## **Rich Niemiec**

Chief Innovation Officer at Viscosity North America

#### Understand & Where to use AI & Machine Learning 101



Conf42 DevSecOps 2023 Thursday • November 30th • 5PM GMT







#### **Rich Niemiec**

#### Oracle ACE Director | CIO

<u>@richniemiec</u>
 <u>linkedin.com/in/richard-niemiec-b65828/</u>
 rich.niemiec@viscosityna.com







@ViscosityNA



#### Oracle License Management Get the most out of your Oracle investment

ZERO DOWNTIME Migrations



Apps Oracle APEX SaaS/Paas Custom Development









On-Call Support Managed Services



#### Viscosity Pillars and Delivery Models

We Enable Business Transformation at a Time When Companies Must Change to Survive!



**Oracle & SQL Server Postgres** Performance Tuning **Data Replication** Data Warehousing Analytics **Data Integration ERP Blue Prints** Database Upgrades

Assessments

viscosityna.com

Workshops



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Managed

Services

#### Viscosity's Oracle ACEs The Oracle ACE Program

The Oracle ACE Program recognizes and rewards individuals for their contributions to the Oracle community.



Charles Kim CEO | Co-Founder

ACE Director



Rich Niemiec Chief Innovation Officer

ACE Director



Craig Shallahamer Applied AI Scientist

ACE Director



GVC

Sean Scott Principal Consultant

A ACE Director

viscosityna.com



Gary Gordhamer Principal Consultant





#### We've written the Books!







## **Quick FREE notes**

## Send email to (for slides): hello@viscosityna.com

(richniemiec@gmail.com)

## @richniemiec - twitter







## Agenda – Apply Technology & W.I.N.

- **Economic Potential of GenAl**
- **Economic Impact of Robots**
- □ ML & Oracle Overview & ADB
- □ Oracle Generative AI Coming
- □ Transformers, ChatGPT & Foundation Models
- □ Oracle Vector DB, GenAI, & Cohere

□ Machine Learning Future, Robots & VR → FYI

richniemiec@gmail.com

viscosityna.com

@richniemiec







## The economic potential of GenAl\*

Digital

The very nature of digital data presents a challenge

⇒

Requires a whole system to create, repurpose, and protect data products

Requires shapeshifting to achieve maximum value Digital Capital and Superstar Firms<sup>1</sup>

12000 9000 3000 1990 2000 2010

Digital capital quantities by market value

Digital capital is more concentrated than any other asset class

of a firm's value is

digital capital

McKinsey & Co.<sup>1</sup>

Most value concentrated in top decile of firms by market value

Digital capital accumulation predicts firm productivity 3 years out

\*Data-driven Transformation, Oracle

## Symbiotic coming Relationship; You & Robots



Courses for Individuals



## Accelerating Digital Transformation with Algorithmic Business Thinking

favorite takeaways, to effectively harness advancements in technologies, organizations need to engineer the human centered genes into their organizations and "take the robot out of the human".

—Martha Anderson Sr. Director, Digital Transformation at Walmart





#### <u>Why generative AI needs a creative</u> <u>human touch</u>

by Beth Stackpole | Jun 5, 2023

Why It Matters

#### MIT EXECUTIVE EDUCATION



#### { Human 🗙 Machine Capability\_

- /\* Today we live, work, and operate, in 2 worlds: physical, and digital
- /\* Combining human and machine capabilities is a multiplier
- /\* Our organizations will evolve in partnership with technology
- /\* By exploring and experimenting, we will evolve our organizations



## The Brain Center at Whipple's & ChatGPT

















## **Robotics/Automation Impact to Jobs**

30%

25%

20%

15%

10%



The New Hork Eimes

#### Uber's Self-Driving Trucks Hit the Highway, but Not Local Roads





#### Low-Income Jobs at Highest Risk Share of workers in occupations at high risk of automa









## Leverage – DB, GPS & Robotics! Impact to Jobs?



## The Obsolete Man

















## **Autonomous Database – Replacing the DBA?**

Rich Niemiec @RichNiemiec · Oct 2

I'll ask #Pepper if she can tune my #database in 11 AM session on #innovation #iot #robotics #cloud at #oow17 #ioug #viscosityna #oracleace



#### Are DBAs Obsolete?

Posted on February 20, 2014

Before we go any further, let me briefly ans "No Way!" OK ... with that out of the way, le

Every so often, some industry pundit gets h "Database administrators are obsolete" or t hear this, it makes me shake my head sadly can be



#### 🛱 Bureau of Labor Statistics

Home 🔻 Subjects 👻 Data Tools 👻 Publications 👻 Econom

#### Economic Releases

#### OCCUPATIONAL OUTLOOK HANDBOOK

Occupational Outlook Handbook > Computer and Information Technology >

#### Database Administrators

Summary	What They Do	Work Environment	How to Become One	Pay	Job

#### Summary

Quick Facts: Database Ad	ministrators		
2017 Median Pay 😨	\$87,020 per year \$41.84 per hour Bachelor's degree		
Typical Entry-Level Education 😨			
Work Experience in a Related Occupation 😨	None		
On-the-job Training 😨	None		
Number of Jobs, 2016 😨	119,500		
Job Outlook, 2016-26 😨	11% (Faster than average)		
Employment Change, 2016-26 😨	13,700		
comprovincine change/ 2010 20 U	15,700		

#### What Database Administrators Do

Database administrators (DBAs) use specialized software to store and organize data, such as information and customer shipping records. They make sure that data are available to users

## Good News: DBA +11% Increase (2016-2026)

## Biju Thomas - Emerging Jobs (Developer/DBA)

#### #8 Data Engineer

2020 Emerging Jobs Report

- 33% annual growth
- Skills
  - Apache Spark
  - Hadoop
  - Python
  - ETL
  - AWS
- Industries
  - Computer Software
  - Information Technology
  - Financial Services
  - Healthcare & Hospitals

- Primary job responsibilities involve preparing data for analytical or operational uses.
- Works as part of an analytics team, providing data in a ready-to-use form to data scientists.
  - scientists.
- Commonly deal with both structured and unstructured data sets

richniemiec@gmail.com

viscosityna.com

@richniemiec

## **Characteristics of Big Data - The Five V's**



#### **Big Data Themes**

- HW & SW technologies for large data volumes
- Focus on Web 2.0 technologies
- Database Scale-out
- Relational & Distributed Data Analytics
- Real Time Analytics

#### Big Data Domains

- Digital Marketing Optimization
- Data Exploration & Discovery
- Fraud Detection & Prevention
- Social Network & Relationship Analysis
- Machine-generated Data Analytics

#### **Converged Database - Oracle Multi-Model Database\***

Benefits of Oracle's Converged Database are broad

\*Slide from Oracle's, Nitin Vengurlekar



- Integrated development tools (Apex, SQL Dev, Spatial Studio)
- 3<sup>rd</sup> party and Open Source development tools
- Machine Learning
- Node.js, Python, many others
- In-memory database
- Spatial, Graph support
- NoSQL (JSON, key-value, wide column, XML)
- Containers, microservices, virtualization (Docker, MT)
- Integrated Security

٠

- Deployment choice (on-prem, cloud, hybrid)
  - Integrated High Availability and Disaster Recovery

## What You Need; Nick of Time (Predictive Analytics)

















#### Percentage of Time Allocated to Machine Learning Project Tasks





echo dot

Add Alexa to any room





Open Sales Dashboard

## A Robot may not look like one!

Oh Yeah... they never complain, always happy to do more, work anywhere, get smarter as time goes on, leverages AI & ML, works 24x7, doesn't ask for a raise, no union (yet).



## A Robot may not look one!

\*Robots that Manage a Database (ADW)!

\*Robots that secure a system and use ML & AI

## Autonomous DB : Future DBA & Robot DB

- Self-Managing (Driving)
- Self-Securing
- Self-Tuning
- Self-Recovering
- Self-Scaling Administration

Fully automated patching, upgrades, backups, & availability architecture



Oracle Unveils World's First Autonomous Database Cloud



## **Oracle Focus:** Cloud, Data, Apps, Security, Self-Service, ML, & Al! Innovation Components for Business!

ORACLE

"I admire risk takers. I like leaders – people who do things before





ORACLE

they become fashionable or popular. I find that kind of integrity inspirational."

LAWRENCE J. ELLISON Chairman & Chief Executive Officer, 2003

ORACLE

## **Oracle Machine Learning: Brief Highlights Only**



richniemiec@gmail.com

viscosityna.com

@richniemiec

## Machine Learning Process (Supervised Learning)

- <u>First</u>: Clear Business Problem to Solve
- <u>Second</u>: *Function* to Perform
- Third: Algorithms to use
- <u>First</u>: Build/*Train the Model:* When you build it use about 60% of your data.
- <u>Second</u>: *Test/Score Model* for accuracy/precision using about 40% of data.

**Compare Algorithms!** 



### **Business Understanding**

#### Be Extremely Specific in Problem Statement:

Poorly Defined	Better	Data Mining Technique
Predict employees that leave	<ul> <li>Based on past employees that voluntarily left:</li> <li>Create New Attribute EmplTurnover → O/1</li> </ul>	
Predict customers that churn	<ul> <li>Based on past customers that left (churn):</li> <li>Create New Attribute Churn → YES/NO</li> </ul>	
Target "best" customers	<ul> <li>Recency, Frequency Monetary (RFM) Analysis</li> <li>Specific Dollar Amount over Time Window:</li> <li>Who has spent \$500+ in most recent 18 months</li> </ul>	
How can I make more \$\$?	<ul> <li>What helps me sell soft drinks &amp; coffee?</li> </ul>	
Which customers are likely to buy?	<ul> <li>How much is each customer likely to spend?</li> </ul>	
Who are my "best customers"?	<ul> <li>What descriptive "rules" describe "best customers"?</li> </ul>	
How can I combat fraud?	<ul> <li>Which transactions are the most anomalous?</li> <li>Then roll-up to physician, claimant, employee, etc.</li> </ul>	x

#### OAA Model Build and Real-time SQL Apply

#### Simple SQL Syntax - Attribute Importance

#### ML Model Build (PL/SQL)



Additional Detail: drop table CUST\_INSUR\_LTV\_SET; exec dbms\_data\_mining.drop\_model('BUY\_INSURANCE\_AI');

create table CUST\_INSUR\_LTV\_SET (setting\_name varchar2(30), setting\_value varchar2(4000));

insert into CUST\_INSUR\_LTV\_SET values
('ALGO\_NAME','ALGO\_SUPPORT\_VECTOR\_MACHINES');
insert into CUST\_INSUR\_LTV values ('PREP\_AUTO','ON');
commit;

#### Model Results (SQL query)

SELECT attribute\_name, explanatory\_value, rank
FROM BUY\_INSURANCE\_AI
ORDER BY rank, attribute\_name;

ATTRIBUTE NAME	RANK	ATTRIBUTE VALUE
BANK FUNDS	1	0.2161
MONEY MONTLY OVERDRAWN	2	0.1489
N TRANS ATM	3	0.1463
N TRANS TELLER	4	0.1156
T AMOUNT AUTOM PAYMENTS	5	0.1095

#### **OAA Model Build and Real-time SQL Apply Prediction**

#### Oracle Advanced Analytics (OAA) Simple SQL - Classification

# BEGIN DBMS\_DATA\_MINING.CREATE\_MODEL( model\_name mining\_function data\_table\_name => 'CUST\_INSUR\_LTV', case\_id\_column\_name => 'CUST\_ID', target\_column\_name => 'BUY\_INSURANCE', settings\_table\_name => 'CUST\_INSUR\_LTV\_SET'); END; /

#### Additional Detail:

drop table CUST\_INSUR\_LTV\_SET; exec dbms\_data\_mining.drop\_model('BUY\_INSUR1'); create table CUST\_INSUR\_LTV\_SET (setting\_name varchar2(30), setting\_value varchar2(4000));

insert into CUST\_INSUR\_LTV\_SET values
('ALGO\_NAME','ALGO\_SUPPORT\_VECTOR\_MACHINE';
insert into CUST\_INSUR\_LTV\_SET values ('PREP\_AUTO','ON');
commit;

#### Model Apply (SQL query)

```
Select prediction_probability(BUY_INSUR1, 'Yes'
```

USING 3500 as bank\_funds, 825 as checking\_amount, 400 as credit\_balance, 22 as age, 'Married' as marital\_status, 93 as MONEY\_MONTLY\_OVERDRAWN, 1 as house\_ownership) from dual;

🖡 📇 🙀 🎭 SQL | All Rows Fetched: 1 in 0.043 seconds

PREDICTION\_PROBABILITY(BUY\_INSUR 1, YES'USING3500ASBANK\_FUNDS, 825ASCHECKING\_AMOUNT, 400ASCREDIT\_BALANCE

1 0.9276956709910801

## DBMS\_DATA\_MINING Oracle Algorithms\*



Algorithm	Abbreviation	Function	*Oracle Database PL/SQL Packages and Types Reference
Apriori	AR	Association	
CUR Matrix Decomposition	CUR	Attribute Im	portance
Decision Tree	DT	Classification	n
Expectation Maximization	EM	Clustering	
Explicit Semantic Analysis	ESA	Feature Extra	action, Classification
Exponential Smoothing	ESM	Time Series	
Generalized Linear Model	GLM	Classification	n, Regression
k-Means	KM	Clustering	
Minimum Descriptor Length	MDL	Attribute Im	portance
Naive Bayes	NB	Classification	n
Neural Networks	NN	Classification	n, Regression
Non-Negative Matrix Factorization	NMF	Feature Extra	action
Orthogonal Partitioning Clustering	O-Cluster	Clustering	
Random Forest	RF	Classification	n
Singular Value Decomposition and Principal Component Analysis	SVD and PCA	Feature Extra	action
Support Vector Machine	SVM	Classification	n, Regression, Anomaly Detection 31

## **DBMS\_DATA\_MINING** Oracle Algorithms \*



ALGO_NAME Value	Description	Mining Function	Those are the <b>actual</b>
ALGO_AI_MDL	Minimum Description Length	Attribute Importance	These are the <b>actual</b>
ALGO_APRIORI_ASSOCIATION_RULE	Apriori	Association Rules	algorithm names
S			that need to be use
ALGO_CUR_DECOMPOSITION	CUR Decomposition	Attribute Importance	that need to be use.
ALGO_DECISION_TREE	Decision Tree	Classification	
ALGO_EXPECTATION_MAXIMIZATION	Expectation Maximization	Clustering	These are values for
ALGO_EXPLICIT_SEMANTIC_ANALYS	Explicit Semantic Analysis	Feature Extraction	ALGO NAME setting
		Classification	
ALGO_EXPONENTIAL_SMOOTHING	Exponential Smoothing	Time Series	
ALGO_EXTENSIBLE_LANG	Language used for extensible algorithm	All mining functions supported	There are <u>many</u>
ALGO_GENERALIZED_LINEAR_MODEL	Generalized Linear Model	Classification, Regression; also Feature Selection and Generation	additional settings
ALGO_KMEANS	Enhanced k_Means	Clustering	that go with each
ALGO_NAIVE_BAYES	Naive Bayes	Classification	Mining Function (i.e.
ALGO_NEURAL_NETWORK	Neural Network	Classification	Confidence, Length,
ALGO_NONNEGATIVE_MATRIX_FACTO R	Non-Negative Matrix Factorization	Feature Extraction	Rules, Aggregates,
ALGO_O_CLUSTER	O-Cluster	Clustering	Cost, Number of
ALGO_RANDOM_FOREST	Random Forest	Classification	Clustersetc.)
ALGO_SINGULAR_VALUE_DECOMP	Singular Value Decomposition	Feature Extraction	,
ALGO_SUPPORT_VECTOR_MACHINES	Support Vector Machine	Classification and Regression *Oracle Database	PL/SOL Packages and Types Reference

## Machine Learning in ADW/ATP - www.oracle.com/cloud/free/



## Machine Learning connection to ADW/ATP

		ADMIN_RICH2 Project [ADMIN_RIC 🔻	ADMIN_RICH2
Build Anomaly Detection model	(1-Class Support Vector Machine)	1	
%script Build Anomaly Detection Model (1-Cla	ass SVM) on CUSTOMERS360 data		
DECLARE v_sql varchar2(100);			
BEGIN			
Create a Build Setting table for Mod	del Build		
EXECUTE IMMEDIATE 'CREATE TABLE CUS' EXECUTE IMMEDIATE 'INSERT INTO CUST EXECUTE IMMEDIATE 'INSERT INTO CUST DBMS_OUTPUT.PUT_LINE ('Created mode	TOMERS360_SET (setting_name VARCHAR2(30),s OMERS360_SET (setting_name, setting_value) OMERS360_SET (setting_name, setting_value) 1 build settings table: CUSTOMERS360_SET '	etting_value_WARCHAR2(4000))); VALUESALGO_NAME'', 'ALGO_SUPPORT_ VALUES (''PREP_AUTO'', ON''); );	/ECTOR_MACHINES
Build the 1-Class SVM model.			
EXECUTE IMMEDIATE 'CALC.DBMS_DATA_M DBMS_OUTPUT.PUT_LINE ('Created mode	INING.CREATE_MODEL(''CUSTOMERS360MODEL''''	"CLASSIFICATION", "CUSTOMERS360", "	CUST_ID '', null, ''CUSTOMERS360_SET'')';
END;	Graph all Customers's PROBABILITY_ANOMAL	OUS vs. YRS_RESIDENCE grouped by CUST_	MARITAL_STATUS
Created model build settings table: CUS Created model: CUSTOMERS360_MODEL PL/SQL procedure successfully completed	<pre>%sql  Click on the bar chart icon and expand settings. Dra  HINT: Select items in the legend to focus on certain of SELECT * FROM (SELECT CUST_ID, round(probability_anomalous,2) prof FROM (SELECT CUST_ID, round(probability_anomalous,2) prof Decomposition of the set of the set</pre>	g PROBABILITY_ANOMALOUS ategories. ability_anomalous, HOUSEHOLD_SIZE, YRS_RESIDENCE, CUST_G	ENDER, CUST_MARITAL_STATUS.
	FROM (SELECT CUST_ID, HOUSEHOLD_SIZE, YRS_RESIDENCE FROM (SUSTOMERS360)) ORDER BY probability_anomalous DESC;	nk , CUST_GENDER, CUST_MARITAL_STATUS, prediction_probabili	ty(CUSTOMERS360MODEL, '0' using *) probability_anomalous
	⊞ 🔐 🏶 🖿 🖉 🖉 🕹 ▾ settings ▾		
	Grouped O Stacked 0.59 0.5 0.4	•Widov	ved Divorc. Mabsent Separ. Married Mar-AF NeverM

## Machine Learning connection to ADW/ATP

$\equiv$	O	RA	<b>CLE</b> <sup>®</sup> Mac	nine Learning		ADM:	IN_RICH2 Project [ADMIN_RIC 🔻 🕄	ADMIN_RICH2	
Displ	ay th	ne top	o 15 most a	anomalous customers				FINISH	60 計團會
%sql Dis	%sql Display the Top 15 Most Anomalous Customers								
SELECT FROM WHERE ORDER	FROM FROM PRK 4 BY pr	CT CUS CUS (SELE FROM = 15 robabi	T_ID, round(p T_GENDER, CUS T CUST_ID, H CUST_MARIT CUSTOMERS360 Lity_anomalou	robability_anomalous,2) probabil T_MARITAL_STATUS, rank() over (0 OUSEHOLD_SIZE, YRS_RESIDENCE, CU AL_STATU <mark>S, prediction_probabilit</mark> )) s DESC;	ity_anomalous, HOUSEHOLD_SIZE RDER BY probability_anomalous MST_GENDER; y(CUSTOMERS360MODEL, '0' usin;	, YRS_RESIDENCE, DESC) rnk ng *) probability_anomalou	us		
	Laul.	G I	View Pr	ediction_Details that expla	in why the record was se	elected as anomalou	s		FINISHED 法 图 变
CUST	_ID	i p	%sql Selec SELECT C	t customers with OCCUPATION of "T UST_ID, TRIM(TRIM(SUBSTR(OUTPRED."Attribu	<pre>FechSup' and more than 55% prot ste1",17,100)), 'rank="1"/&gt;') Fi </pre>	bability of being anomalo	us		
10019	9	<pre>RTRIM(TRIM(SUBSTR(OUTPRED."Attribute2",17,100)),'rank="2"/&gt;') SECOND_ATTRIBUTE, RTRIM(TRIM(SUBSTR(OUTPRED."Attribute3",17,100)),'rank="3"/&gt;') THIRD_ATTRIBUTE, RTRIM(TRIM(SUBSTR(OUTPRED."Attribute4",17,100)),'rank="4"/&gt;') FOURTH ATTRIBUTE.</pre>			HIRD_ATTRIBUTE, OURTH_ATTRIBUTE,				
10294	102948 0.7			IFTH_ATTRIBUTE USING	ILS FROM CUSTOMERS360				
10113	7	C	.6	AND OCCUPATION = TRANSAP 6 ORDER BY CUST_ID) OUT,					
10/35	à	0	CUST_ID	FIRST_ATTRIBUTE		SECOND_ATTRIBL	JTE	THIRD_ATTRIBUTE	
			100646	"CUST_MARITAL_STATUS" ac weight=".226"	tualValue="Widowed"	"CUST_YEAR_OF_	BIRTH" actualValue="1941" weight=".11	8" "CUST_CREDIT_LIMI	IT" actual√alue="1500" weight=".
			102922	"CUST_MARITAL_STATUS" ac weight=".222"	tualValue="Widowed"	"CUST_YEAR_OF_ weight=".169"	BIRTH" actualValue="1931"	"CUST_CREDIT_LIMI	IT" actual√alue="1500" weight=".
			103441	"CUST_MARITAL_STATUS" ac weight=".222"	tualValue="Widowed"	"CUST_YEAR_OF_	BIRTH" actualValue="1941" weight=".11	7" "EDUCATION" actual\	/alue="Bach." weight=".076"
			104286	"EDUCATION" actual/value="9th	h" weight=".165"	"HOUSEHOLD_SIZ	E" actual√alue="4-5" weight=".146"	"CUST_CREDIT_LIMI	IT" actual∨alue="1500" weight=".

#### A Game of Pool (Talent / Luck / Work / Nerve) (Your Current Team Plays Robots built on the Best Past Teams or ML)







#### Gambling on virtual reality: the online casinos of the future



Image Credit: SlotsMillion






- Naïve Bayes
- Logistic Regression (GLM)
- Decision Tree
- Random Forest
- Neural Network
- Support Vector Machine (SVM)
- Explicit Semantic Analysis
- XGBoost\*

#### ANOMALY DETECTION

- One-Class SVM
- MSET-SPRT\*

#### CLUSTERING

- Hierarchical K-Means
- Hierarchical O-Cluster
- Expectation Maximization (EM)

### TIME SERIES MAMAM

- Forecasting Exponential Smoothing
- Includes popular models e.g. Holt-Winters with trends, seasonality, irregular time series

#### **OML** Algorithm Cheat Sheet Algorithm Documentation



- Generalized Linear Model (GLM)
- Support Vector Machine (SVM)
- Stepwise Linear regression
- Neural Network
- XGBoost\*



- Minimum Description Length
- Random Forest
- Unsupervised Pairwise KL Divergence
- CUR decomposition for row & AI

#### ASSOCIATION RULES



A priori

### **SOL** ANALYTICS

- SOL Windows SOL Patterns
- SQL Aggregates



#### FEATURE EXTRACTION

- Principal Comp Analysis (PCA)
- Non-negative Matrix Factorization
- Singular Value Decomposition (SVD)
- Explicit Semantic Analysis (ESA)

#### **ROW IMPORTANCE**

CUR Decomposition

#### RANKING

XGBoost



#### TEXT MINING SUPPORT

- Algorithms support text columns
- Tokenization and theme extraction
- Explicit Semantic Analysis (ESA)

#### STATISTICAL FUNCTIONS

 min, max, median, stdev, t-test, F-test, Pearson's, Chi-Sq, ANOVA, etc.

Includes support for partitioned models. integrated text mining, automated data preparation

\* New in 21c





## **Decision Tree Algorithm (ML Classifier)**

- Tree model for decisions
- Decisions made to reach goal
- Calculate odds of different choices
- Can have chance outcomes
- Calculate costs & utility (value)

 Could be used for chatbots (to answer questions) Flow Chart calculates when to settle a case or not based on costs/probabilities



## OML (OAA) Oracle Data Mining SQL Sample (PARTIAL)

## dmdtdemo.sql =DBMS\_DATA\_MINING package - Decision Tree



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## Random Forest (ML Classifier)

- Multitude of Decision Trees (picks the mode)
- Output: Class of decision tree most likely
- *Mode* of the classes is mean or *most likely*
- Mode is found during training time
- Separate the Real Data from the Noise! (divide and conquer)
- Fix decision tree "overfitting" or <u>"too close of fit"</u> with supervised learning training set.
- Miss outliers if overfitting occurs
- Bagging smooths things out





Tally: Six 1s and Three 0s Prediction: 1

## Neural Network (ML Classifier)

- Artificial Neural Networks (ANN) make ML/AI fast
- <u>Deep Learning</u> (Google's **Tensor Flow** leverages this)
- Image Classification with Tensor Flow
- Classify patterns & sequences, regression testing...
- Data Mining, Spam Filtering, Robotics
- Supervised or Unsupervised Learning
- Autonomous Vehicles
- Use for Predictive Modeling
- Used with Speech Recognition



## **Neural Network (ML Classifier): Pixels**

Machine Learning **Foundation Models** "how" Features **functionalities** learning algorithms architectures models



Massachusette Institute of

**Biological Neural Network** 



Use BP or <u>Backpropagation</u> to update weights to minimize loss; use gradient descent or stochastic gradient descent [ differential]. (PyTorch autograd / Dropout so you don't overfit)

NN's also called ANN's /Artificial Neural Networks

### AI Neural Network



y = vector/image

W=weight (each line weight/strength)

- **b** = thresholds/vector or bias
- y times W is just Vector x Matrix
- h = rectified linear unit (>0)

Set: #layers / W's / b's / #neurons / features

## Neural Network - CNN (ML Classifier)\* \*HeliFromFinland

### Convolutional Neural Networks (CNN, or



needed-over-traditional-machine-learning-1b6a99177063

#### CLASSIFICATION



- Naïve Bayes
- Logistic Regression (GLM)
- Decision Tree
- Random Forest
- Neural Network
- Support Vector Machine (SVM)
- Explicit Semantic Analysis
- XGBoost\*

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\* New in 21c





## **One-Class SVM (ML Anomaly Detection)**

- Support Vector Machine (SVM)
- One-Class Classification (OCC)
- Used to Classify Data
- Supervised Learning using Algorithms
- Identify specific objects of a class based on supervised learning based on objects of that class.
- SVM maps training data into separated areas
- Unsupervised Learning does data clustering
- They analyze the data used for **regression**
- SVM as binary non-probabilistic linear classifier
- Classify images, text, & even hand written text.



Fraud detection Use SVM OCC

## **One-Class SVM (ML Anomaly Detection)\***



The hypersphere containing the target data having center a and radius R. Objects on the boundary are support vectors, and two objects lie outside the boundary having slack greater than 0.

**Support Vector Data Description (SVDD)**: Find the smallest hypersphere containing all data points (use supervised training to get it)



Linear SVM



viscosityna.com

@richniemiec \*Wikipedia

## Smart Anomaly Detection with MSET2 (SAM)

Created by nuclear scientists to analyze physical systems



All 90+ US nuclear reactors and most of the 450 reactors worldwide use MSET for prognostic analytics in safety systems



Oracle Exadata machines and Oracle Cloud use MSET for predictive maintenance, helping to deliver highest cloud uptime in the industry



Major airlines use MSET in jet engines for predictive health monitoring, benefiting uptime, maintenance activities, and supply chain costs

#### CLASSIFICATION



- Naïve Bayes
- Logistic Regression (GLM)
- Decision Tree
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- Neural Network
- Support Vector Machine (SVM)
- Explicit Semantic Analysis
- XGBoost\*

#### ANOMALY DETECTION

- One-Class SVM
   MSET-SPRT\*
  - VI minter and
- CLUSTERING
  - Hierarchical K-Means



- Hierarchical O-Cluster
- Expectation Maximization (EM)

### TIME SERIES MANA

- Forecasting Exponential Smoothing
- Includes popular models

   e.g. Holt-Winters with trends,
   seasonality, irregular time series

#### OML Algorithm Cheat Sheet Algorithm Documentation



- · Generalized Linear Model (GLM)
- Support Vector Machine (SVM)
- Stepwise Linear regression
- Neural Network
- XGBoost\*



- Minimum Description Length
- Random Forest
- Unsupervised Pairwise KL Divergence
- CUR decomposition for row & AI

#### **ASSOCIATION RULES**



A priori

### SQL ANALYTICS

- SQL Windows
  SQL Patterns
- SQL Aggregates



#### FEATURE EXTRACTION

- Principal Comp Analysis (PCA)
- Non-negative Matrix Factorization
- Singular Value Decomposition (SVD)
- Explicit Semantic Analysis (ESA)

#### **ROW IMPORTANCE**

CUR Decomposition

#### RANKING

XGBoost\*



#### TEXT MINING SUPPORT

- Algorithms support text columns
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### STATISTICAL FUNCTIONS

• min, max, median, stdev, t-test, F-test, Pearson's, Chi-Sq, ANOVA, etc.

Includes support for partitioned models, integrated text mining, automated data preparation

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## **Hierarchical K-Means (ML Cluster)**

- Use the K-means (Lloyd's) Algorithm
- Use observations of the Data Set
- Clusters generated based on each observation with nearest mean & <u>hierarchies of clusters</u>.



How Many? Elbow Method (4 in image)!

Centroid cluster is new mean - <u>Repeat</u>



## **Oracle Analytics Cloud (OAC) to Cluster Data**



# **Hierarchical O-Cluster (ML Cluster)**

- Orthogonal Partitioning Clustering
- Oracle-Proprietary clustering algorithm
- Algorithm operates recursively
- Creates dense areas in attribute space



- Hierarchical grid-based with Axis-parallel (orthogonal) partitions
- Sensitivity defines baseline density level (to separate peaks/valleys)
- Areas with peak density above baseline are clusters
- Clusters used to generate Bayesian probability
- Outliers can cause issue; pre-clip outliers
- <u>K-Means is Distance Based; O-Cluster is Density Based!</u>

#### CLASSIFICATION



- Naïve Bayes
- Logistic Regression (GLM)
- Decision Tree
- Random Forest
- Neural Network
- Support Vector Machine (SVM)
- Explicit Semantic Analysis
- XGBoost\*

#### ANOMALY DETECTION

- One-Class SVM
- MSET-SPRT\*

#### CLUSTERING

- Hierarchical K-Means
- Hierarchical O-Cluster
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#### ASSOCIATION RULES A priori

#### **SOL** ANALYTICS

- SOL Windows SOL Patterns
- SQL Aggregates



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\* New in 21c







## Seasonal, Irregular & Missing Data: Time Series Algorithm



Week

#### CLASSIFICATION



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- Random Forest
- Neural Network
- Support Vector Machine (SVM)
- Explicit Semantic Analysis
- XGBoost\*

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- 0 0
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#### OML Algorithm Cheat Sheet Algorithm Documentation

- REGRESSION
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  - Neural Network
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## Association Rules A priori

#### SQL ANALYTICS

- SQL Windows
  SQL Patterns
- SQL Patterns
   SQL Aggregates



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XGBoost\*



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\* New in 21c





## Linear Model (Regression)

### Linear Regression (below):

Using simple **Linear Regression** we find the line between the points. There is one independent and one dependent variable. This helps us get to predictive analytics.



Linear Regression (above): Unemployment goes down & GDP goes up



## **Generalized Linear Model (GLM)**

- GLM: Flexible generalization of linear regression
- GLM allows output that doesn't match normal linear regression & generalizes it by a link function based on variance from predicted value.
- GLM for varying <u>situations without Normal</u>
   <u>Distributions</u>
- GLM assumes observations uncorrelated
- GLM assumes random vs. normal effects
- GLM mixed models allow random effects that can be correlated through some probability.



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#### **OML** Algorithm Cheat Sheet Algorithm Documentation



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- TTRIBUTE MPORTANCI
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#### ASSOCIATION RULES



A1 A2 A3 A4 A5 A6 A7

A priori

#### **SOL** ANALYTICS

- SOL Windows



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XGBoost



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- SOL Patterns
- SQL Aggregates



## Principal Component Analysis (Attribute Importance)

- PCA: A dimension-reduction tool taking large set of attributes to small set (reduction) with most important information.
- Use Feature Selection of Most Important Attributes
- PCA speeds up your ML reducing dimension input
- "The eigenvectors and eigenvalues of a covariance (or correlation) matrix are the "core" of PCA and...
- The **eigenvectors** (principal components) determine the directions of the new feature space, and the **eigenvalues** determine their magnitude."
- PCA is the simplest eigenvector based analysis (multivariate)

(see next slide for example & later slides for example on PCA Feature Extraction)

## Living Doll

















#### These dolls are spying on your kids, consumer groups say



By Doug Criss, CNN Published 3:46 PM EST, Thu December 8, 2016







"Privacy advocates try to keep 'creepy,' 'eavesdropping' Hello Barbie from hitting shelves," Sarah Halzack, Washington Post

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A1 A2 A3 A4 A5 A6 A7

#### A priori

#### SQL ANALYTICS

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# **Apriori / Market Based (Association Rules)**

- Apriori Algorithm is used for <u>association rule</u> <u>learning</u> databases. <u>Oracle Excels here!</u>
- Identifies <u>frequently associated</u> database items



- Frequent items determine <u>Association Rules (trends)</u>
- Helps with <u>Market Basket analysis (purchase</u> <u>behavior of customers</u> (retail) by using information to discount/promote items
- Also shows items bought together (cheese/crackers)
- The algorithm may scan database many times (downside)
- Finds too many matches (must limit this at times)

## A Priori / Market Based (Association Rules)



<u>T4Tutorials</u>: Finding best Items Frequently Bought together. <u>Emory Univ. CS:</u> Maybe we don't need the beer that close to the Bread, Diapers & Milk

#### CLASSIFICATION



- Naïve Baves
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- Decision Tree
- Random Forest
- Neural Network
- Support Vector Machine (SVM)
- Explicit Semantic Analysis
- XGBoost\*

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A1 A2 A3 A4 A5 A6 A7

#### SOL ANALYTICS

- SQL Windows SOL Patterns
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## Singular Value Decomposition (Feature Extraction)



## **Principal Component Analysis (Feature Extraction)**

- PCA Feature extraction reduces large data sets, by building new set of attributes making it faster to process
- **Present** the <u>same information with Fewer Variables</u>
- Ensure you preserve the structure (variance)
- Use Feature Extraction vs. Feature Selection



Visual Feature Extraction Extract features from the face that can be used for the recognition task

- PCA is a dimension-reduction tool taking large set of variables to small set with most important information.
- First component has largest variance and succeeding variables are orthogonal & highest variance.
- PCA uses orthogonal transformation to convert possibly correlated variables (numeric) into linear uncorrelated variables (principle components)
- New Attributes a Combination of Old Attributes



## In His Image (Available Now - 100K+ Waiting List)







#### ETE<sub>7</sub>9

#### The most daring experience ever made on the Internet.

Let your counterpart work for you. The very first-ever intelligent virtual self of you.

#### **DDOUBLE YOURSEL**

Currently, we have over 100,000 registered users who are on the waiting list for ETER9 brainchild: **dd**uplicata. Be a part of this remarkable phase too!

#### OCBS Aol. BBC The Telegraph theguardian Stin

#### 🗵 🕣 🛅 🖸



#### Artificial Intelligence

ETER9 is a social network that relies on Artificial Intelligence as a central element, and it's currently in the BETA stage. Even in your absence, the virtual beings will publish, comment and interact with you intelligently.



#### Counterpart

The Counterpart is your Virtual Self that will stay in the system and interact with the world just like you would if you were present. Your Counterpart will learn more with each action you take. The more you interact in the new social network, the more your Counterpart will learn!



#### **Cyber Eternity**

Eternizing is a way of keeping your thoughts and posts for all time. Are you curious?Come meet your Counterpart and become eternal. Challenge the impossible.

## Number 12 Looks Like You (2020)





TikToker Goes Viral By Exposing The Truth Behind Heavily-Edited Pictures

TikTok guidelines said not to promote posts by 'ugly' and poor users



Camouflage Makeup - Amazon.com



hide or disguise the presence of



AFTER





BUILI





#AgeChallenge





#### CLASSIFICATION



- Naïve Baves
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- Explicit Semantic Analysis
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#### ASSOCIATION RULES A priori



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#### ROW IMPORTANCE

CUR Decomposition

#### RANKING

XGBoost\*



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Includes support for partitioned models. integrated text mining, automated data preparation



#### **OL** ANALYTICS SQL Windows

- SOL Patterns
- SQL Aggregates



## SQL Analytics (Windows / Patterns / <u>Aggregates</u>)\*



\*Oracle Docs



#### CLASSIFICATION



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## Statistical Functions in Oracle (Partial List)\*

Numeric Functions	Analytic Functions		Aggregate Functions		Data Mining Functions
ABS ACOS ASIN ATAN ATAN2 BITAND CEIL COS COSH EXP FLOOR LN LOG MOD NANVL POWER REMAINDER ROUND (number) SIGN SIN SIN SIN SIN SINH SQRT TAN TANH TRUNC (number) WIDTH_BUCKET	AVG * CLUSTER_DETAILS CLUSTER_DISTANCE CLUSTER_ID CLUSTER_PROBABILITY CLUSTER_SET CORR * COUNT * COVAR_POP * COVAR_SAMP * CUME_DIST DENSE_RANK FEATURE_DETAILS FEATURE_ID FEATURE_SET FEATURE_SET FEATURE_VALUE FIRST FIRST_VALUE * LAG LAST_VALUE * LEAD LISTAGG	MAX * MIN * NTH_VALUE * NTILE PERCENT_RANK PERCENTILE_CONT PERCENTILE_DISC PREDICTION PREDICTION_COST PREDICTION_DETAILS PREDICTION_PROBABILITY PREDICTION_PROBABILITY PREDICTION_SET RANK RATIO_TO_REPORT REGR_ (Linear Regression) ROW_NUMBER STDDEV * STDDEV * STDDEV * STDDEV SAMP * VAR_POP * VAR_SAMP * VARLANCE *	APPROX_COUNT APPROX_COUNT_DISTINCT APPROX_COUNT_DISTINCT_AGG APPROX_COUNT_DISTINCT_DETAIL APPROX_MEDIAN APPROX_PERCENTILE APPROX_PERCENTILE_AGG APPROX_PERCENTILE_DETAIL APPROX_RANK APPROX_SUM AVG COLLECT CORR CORR_* COUNT COVAR_SAMP CUME_DIST DENSE_RANK FIRST GROUP_ID GROUPING GROUPING GROUPING_ID JSON_ARRAYAGG JSON_OBJECTAGG LAST LISTAGG MAX	MEDIAN MIN PERCENT_RANK PERCENTILE_CONT PERCENTILE_DISC RANK REGR_(Linear Regression) Function STATS_BINOMIAL_TEST STATS_CROSSTAB STATS_F_TEST STATS_KS_TEST STATS_MODE STATS_MODE STATS_MW_TEST STATS_ONE_WAY_ANOVA STATS_T_TEST_* STATS_ONE_WAY_ANOVA STATS_T_TEST_* STATS_ONE_WAY_ANOVA STATS_T_TEST_* STDDEV STDDEV_POP STDDEV_SAMP SUM SYS_OP_ZONE_ID SYS_XMLAGG TO_APPROX_COUNT_DISTINCT TO_APPROX_PERCENTILE VAR_SAMP VAR_SAMP VARIANCE XMLAGG MEDIAN PROSE ALSO: T-Test (Analysis of	CLUSTER_DETAILS CLUSTER_DISTANCE CLUSTER_ID CLUSTER_PROBABILITY CLUSTER_SET FEATURE_COMPARE FEATURE_DETAILS FEATURE_ID FEATURE_SET FEATURE_VALUE ORA_DM_PARTITION_NAME PREDICTION_BOUNDS PREDICTION_BOUNDS PREDICTION_COST PREDICTION_DETAILS PREDICTION_PROBABILITY PREDICTION_SET

\* Oracle Database SQL Language Reference

## Machine Learning Functions\* - Oracle Docs.

- <u>First</u>: Clear Business Problem to Solve
- <u>Second</u>: *Function* to Perform
- Third: Algorithm to use
- <u>First</u>: Build/*Train the Model* when you build it using about 60% of data.
- <u>Second</u>: *Test/Score Model* for accuracy/precision using about 40% of data.

**Compare Algorithms!** 


## AutoML is here for Autonomous Database

#### ORACLE<sup>\*</sup> Machine Learning III ML USER Project [ML USER Works... V <- Experiments eader Board AutoML Rich Create Notebook Metrics Deploy Experiment Settings Zedit Algorithm Model Name Accuracy Accuracy Support Vector Machine (Gaussian) svmg\_09cd02ee4e 0.7878 0.790 rf df53fb31a8 Random Forest 0.7821 0.780 Generalized Linear Model glm\_74cbb2b7ac 0.7821 0.760 Generalized Linear Model (Ridge Regres... glmr df24288679 0.7821 Support Vector Machine (Linear) svml\_a031bb0ae1 0.7431 Leader Board Metrics Create Notebook × Algorithm Model Name Accuracy Create a notebook based on selected model and this experiment's settings. Use a generated notebook to further tune your approach using Python. Support Vector Machine (Gaussian) svmg\_09cd02ee4e 0.7878 Notebook Name: Random Forest rf df53fb31a8 0.7821 AutoML\_Classify Generalized Linear Model glm\_74cbb2b7ac 0.7821 ? OK Cancel Generalized Linear Model (Ridge Regres... glmr df24288679 0.7821

0.7431

Support Vector Machine (Linear) svml\_a031bb0ae1



```
svm mod = svm mod.fit(X train. v train)
```

\*

### Time Enough at Last for ML with AutoML



#### Exadata Cloud Machine: ALL Features (X10M is Out - 1T/sec!) (Oracle's Juan Loaiza presentation on Exadata Cloud; X10M has > 2P Flash)

Exadata Cloud: Compatible, Scalable, Available, Secure Decades of Database Innovation Proven at Millions of Mission-Critical Deployments



## Machine Learning & AI - Oracle's Built-In Algorithms 21

### **Oracle Machine Learning Algorithms**

#### CLASSIFICATION

Naïve Bayes Logistic Regression (GLM) Decision Tree Random Forest Neural Network Support Vector Machine Explicit Semantic Analysis XGBoost\*

#### CLUSTERING

Hierarchical K-Means Hierarchical O-Cluster Expectation Maximization (EM)

#### **ANOMALY DETECTION**

One-Class SVM MSET-SPRT\*

#### TIME SERIES

Forecasting - Exponential Smoothing Includes popular models e.g. Holt-Winters with trends, seasonality, irregularity, missing data



#### REGRESSION

Linear Model Generalized Linear Model Support Vector Machine (SVM) Stepwise Linear regression Neural Network XGBoost\*

#### ATTRIBUTE IMPORTANCE

Minimum Description Length Principal Comp Analysis (PCA) Unsupervised Pair-wise KL Div CUR decomposition for row & Al

Association Rules A priori/ market basket

PREDICTIVE QUERIES Predict, cluster, detect, features

#### SQL ANALYTICS

SQL Windows SQL Patterns SQL Aggregates





SQL>\_

#### **FEATURE EXTRACTION**

Principal Comp Analysis (PCA) Non-negative Matrix Factorization Singular Value Decomposition (SVD) Explicit Semantic Analysis (ESA)

#### TEXT MINING SUPPORT



#### STATISTICAL FUNCTIONS



R

Basic statistics: min, max, median, stdev, t-test, F-test, Pearson's, Chi-Sq, ANOVA, etc.

#### R & PYTHON \* Coming soon

Third-party R & Python Packages through Embedded Execution Spark MLlib algorithm integration

#### MODEL DEPLOYMENT & MONITORING

SQL—1<sup>st</sup> Class Objects Oracle RESTful API (ORDS) OML Web Services (for Apps) \* New in **21**<sup>c</sup>



#### \*XGBoost for Classification, Regression & Ranking

 $\frown$ 

# Biju Thomas at ODTUG - Emerging Jobs

#### #1 AI / ML Specialist (Engineer)

Linkedin

2020 Emerging Jobs Report

- 74% annual growth
- Skills
  - Machine Learning
  - Deep Learning
  - TensorFlow
  - Python
  - Natural Language Processing
- Industries
  - Computer Software
  - Information Technology
  - Higher Education
  - Consumer Electronics

- Take the data scientists' code and making it more effective and scalable.
- Introduce various programming rules and good practices.
- Join the results from potentially unrelated tasks to enhance the models performance even more.
- Glue all the "data science" and "software" parts together.

richniemiec@gmail.com

viscosityna.com

## ML & Business Apps



## **Applications - Al Powered; Analytics & ML**

#### **E-Business Analytics Accelerator: Pre-built solutions to speed insights**



100s of Pre-built Dashboards

-10-

	Outcomes
Financials	<ul> <li>Profitability drivers</li> <li>Improve use of working capital</li> <li>Control business expenditures</li> </ul>
Supply Chain	<ul> <li>Improve efficiency</li> <li>Reduce costs</li> <li>Ensure customer satisfaction</li> </ul>
нсм	<ul> <li>Complete view of employees</li> <li>Identify best resources</li> <li>Identify attrition factors and predict risk</li> <li>Cross-domain reporting</li> </ul>

### **Oracle GenAl**

#### Oracle Database Vision With Generative AI (LLM)

\* Sign up to preview Al Vector Search

Make it easy to generate and run modern apps and analytics for all use cases at any scale

### Oracle Database 23c

Sample of Marquee Features for DBAs, Analysts, & Developers

Now <b>GA</b> on OCI Base Database Service	DBA		Real-time SQL Plan Management SQL Firewall True Cache	
	ANALYST	é dia	Automatic Materialized Views Improved ML Algorithms	
NEW IN 23c	DEVELOPER		JSON Duality Views Property Graph Views JavaScript Stored Procedures SQL Domains Al Vector Search* (coming soon)	0

# SQL Generation from Natural Language *using LLM*





### Think of it as an Assistant (60-70%)



What's next from Oracle Data Management

# Example of a **Prompt**

**Instructions:** You are an Oracle SQL expert. Given an input question, first create a syntactically correct Oracle SQL query to run. You must query only the columns that are needed to answer the question. **Pay attention** to use only the column names you can see in the tables below. Be careful to not query for columns that do not exist. Also, pay attention to which column is in which table.

Use the following format: Question: Question here SQL: Generated SQL query

Context: Only use the following tables and columns

Table: HR.DEPARTMENTS, Columns: DEPARTMENT\_ID, DEPARTMENT\_NAME, MANAGER\_ID, LOCATION\_ID Table: HR.EMPLOYEES, Columns: EMPLOYEE\_ID, FIRST\_NAME, LAST\_NAME, SALARY, MANAGER\_ID, DEPARTMENT\_ID Primary keys: HR.DEPARTMENTS.DEPARTMENT\_ID, HR.EMPLOYEES.EMPLOYEE\_ID Foreign keys: HR.EMPLOYEES.DEPARTMENT\_ID -> HR.DEPARTMENTS.DEPARTMENT\_ID, HR.DEPARTMENTS.MANAGER\_ID -> HR.EMPLOYEES.EMPLOYEE\_ID

**Question:** Give me the average salary of employees in each department SQL:

### Think of it as an Assistant (60-70%)

APEX App Builder      SQL Workshop      Team Development	nt 😪 Gallery	Q. Search	2, 0 DE
↑ Utilities \ Quick SQL			
Settings saved		What's next from	
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#### In whole example: He wrote 47 lines & it built 1200





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What's next from Oracle Data Management

Q & demo

k

#### = My Awesome App

#### **Employees**





### APEX THE low code Dev Tool: 2M APEX Apps = 3K/day

### **IDC Survey Spotlight**

Regardless of your organization's maturity with low code/no code app dev, which of the following platforms does your organization predominantly utilize today (or would likely use in the next 24 months) to build low code/no code applications?



# **GenAl Writes the SQL**

Generative AI can't generate a complete solution

It generates a first draft that experts validate and evolve



## GenAl will get to the End-User in ALL products



#### What's next: A Worldwide race to build Al.



Generative AI Changes Everything Infrastructure & Applications



#### Is GenAl Most Important Ever? You're About to Find Out!





### Healthcare Driving Oracle to Better Al Products

# IoT Sensors: Collect Huge Amounts of Al Training Data Healthcare Training Data: Some Data Not Saved

- Patient Monitoring: Blood Pressure, Pulse Oximeter, Smart Watch
- Diagnostic Images: X-Rays, MRI Scans, Biopsy Slides ...
- Genomics: Gene Sequences, Variations and Mutations

#### Diagnostic Image Storage Cost Problem

- Diagnostic Images & Genomics: Not Saved Due to Cloud Storage Costs
- Oracle Cloud: Provides an Economic Solution to this Problem



## **Oracle Driving First Responders with Tesla**



# **OpenAl - Ten Years Later... the Baby Talks!**

#### HOW LONG IT TOOK TOP APPS TO HIT 100M MONTHLY USERS

ChatGPT is estimated to have hit 100M users in January, 2 months after its launch. Here's how long it took other top apps to reach that:

MONTHS TO REACH 100M GLOBAL MAUS

APP

\$ CHATGPT 2 d TIKTOK 9 0 30 INSTAGRAM 0 41 PINTEREST 55 3 SPOTIFY *TELEGRAM* 61 Ð UBER 70 GOOGLE 78 TRANSLATE vahoo! SOURCE: UBS

About One Year Ago: ChatGPT 3.5 was Born ... the Baby Talks

- Developed by OpenAl: A Company Founded by Elon Musk 10 Years Ago
   Huge Artificial Neural Network: Multi-Billion Parameter Large Language Model (LLM)
- Trained on Language: Trillions of Data Elements ... Wikipedia + Public Internet
- ChatGPT 3.5 Talks: Generates Answers to Questions ... Engages in Conversations

#### A Big Surprise ChatGPT's Scale Enabled it to Understand and Generate Language



Unlike ChatGPT, GPT-4 can see and understand images, whereas the former is limited to text.

While ChatGPT had several issues upon its arrival, Microsoft claims that GPT-4 has been trained to avoid several malicious prompts.

# Generative AI - Things to Know...

- ChatGPT predicts the next word ... looks at less stuff.
- Oracle announces Vector DB to store words, images+ & use LLM to search
- LLM's Every Text / Email has auto-complete; translate languages, using a NN
- GenAI, LLM, ChatGpt (Generates News, articles, etc.)
- Will get us to AGI Artificial Generative Intelligence. Language gets us to AGI.
- **"Time of Exponential Development"** Similar to how Computers started to Exponentially get bigger & faster.
- We use language even when thinking about something
- LLM's are predictive machines, training data of Wikipedia & the Internet
- 100 layers of neurons for ChatGPT4 But, still can "Hallucinate"
- Trains the NN by reading the internet ... etc.
- GenAI, Gpt4 (LLM), DeepMind WaveNet (text to audio), OpenAI DALL\*E 2 -(text to images), Google DeepMind Google AlphaFold (phara - protein folding same timing as ChapGPT 3.5) discoveries, ChatPDF, SlideGPT, MusicLM

# ChatGPT

#### GPT-4 has arrived. It will blow ChatGPT out of the water The Washington Post 3/14/2023

ChatGPT was launched on November 30, 2022, by San Francisco-based OpenAl (the creator of the GPT series of large language models; DALL. E 2, a diffusion model used to generate images; and Whisper, a speech transcription model).





limited to text.

While ChatGPT had several issues upon its arrival, Microsoft claims that GPT-4 has been trained to avoid several malicious prompts.

- tolerance.
- 10. Amazon DynamoDB: A fully mana S Regenerate response vice provided by Amazon Web

amounts of data across commodity servers and providing high availability and fault

# **Google's Bard**

Bard (Experiment)

- Reset chat
- Bard Activity
- FAQ
- E Updates
- ! Help

Illinois, USA

From your IP address - Update location



Here is a brief overview of each of the top 10 databases:

- Oracle is a commercial database that is known for its scalability and performance. It is often used by large enterprises that need to store and manage large amounts of data.
- MySQL is an open-source database that is known for its ease of use and flexibility. It is often used for web applications and other
  applications that need to be scalable and easy to maintain.
- Microsoft SQL Server is a commercial database that is known for its integration with other Microsoft products. It is often used by businesses that use Microsoft's Windows operating system and other Microsoft products.
- PostgreSQL is an open-source database that is known for its power and flexibility. It is often used for applications that need to store complex data or that need to be highly scalable.
- MongoDB is a NoSQL database that is known for its flexibility and scalability. It is often used for applications that need to store large amounts of unstructured data.
- Redis is a NoSQL database that is known for its speed and performance. It is often used for applications that need to store and manage large amounts of data in real time.
- IBM DB2 is a commercial database that is known for its scalability and performance. It is often used by businesses that need to store and manage large amounts of data.
- Elasticsearch is a search engine database that is known for its speed and scalability. It is often used for applications that need to search and index large amounts of data.
- Cassandra is a NoSQL database that is known for its scalability and fault tolerance. It is often used for applications that need to store and manage large amounts of data in a distributed environment.
- MariaDB is a fork of MySQL that is known for its stability and performance. It is often used as a replacement for MySQL when MySQL is not available or when a more stable database is needed.

Enter a prompt here



Bard

Bard may display inaccurate or offensive information that doesn't represent Google's views.

## Transformers - Google, 2017



N×



#### Leverages Parallelism to train model

## **Transformer Model led to Dominant Design**

• All main models today are transformer models

#### The Transformer Architecture: Gene®openAI dominant design?





# **Generative AI: GPT & ChatGPT**

- **GPT = Generative Pre-trained Transformer**
- ChatGPT is a Foundation Model (Stanford paper 2021/2022) for LLM (Large Language Model) Chatbots. At end of 2018, NLP changed with start of foundation models begins.
- Transformer model architecture [Vaswani et al. 2017] that leverages the parallelism of the hardware to train much more expressive models than before.
- Foundation models have also led to surprising emergence which results from scale. For example, GPT-3 [Brown et al. 2020], with 175 billion parameters compared to GPT-2's 1.5 billion, permits in-context learning. (DALL-E for images)
- GPT-4 is 1 trillion parameters & you refine using your data.
- GenAl Generates new content/output (GANs & Deep Fake)

### ChatGPT-4



dataset construction, training method, or similar.

# ChatGPT 4 is Bi-Modal (Images/Words)







Here are eight images:



The following image is:

What's in this picture?

That's not a duck. Then

Why?

Looks like a duck.

Looks more like a

bunny.

what's it?

unny ears







this photo is funny? Answer:

The cat is wearing a mask that gives the cat a smile.

Carbon and a diverse of the summary state in the

What is TorchScale?

(1)

broke. (2)



Question: The result is? Answer:

5 + 4 = 9

(6)

A Ebrary that allows transformers to work efficiently and effectively at any scale. (5)



Question: Why did the little boy cry? Answer

Because his scooler



pony tail

(3)

57

57 bpm

(7)



**GPT - 4** 

Question: What is the hairstyle of the blond movie be released? called? Answer.

Answer: On June 27

(4)



Question: What is the heart rate in this picture? Answer



10:10 on a large clock

(8)
### **Oracle Vector Database Introduced!**

- Oracle Vector Database: Easily Specialize Al Models & Build Al Apps Designing & Training Foundational AI Models: Complex and Expensive

  - Design Multi-Billion Parameter Artificial Neural Network: OpenAl, Cohere, xAl ...
  - Ingest Trillions of Training Data Elements: Wikipedia + Everything on the Internet Oracle Cloud: 16,000 Node H100 NVIDIA Supercluster with RDMA Interconnect
  - Specializing Al Models: Pretrained Foundational Model + Supplementary Training Data •
    - Oracle Vector Database: Stores Vectorized Supplementary Training Data
    - Specialized AI Model with EHR Data: Generate Doctors' Orders Cerner New Millennium •
    - Specialized AI Model with Diagnostic Image Data: Rapid Cancer Detection Imagene .

Most Customers will Train Specialized AI Models for Specific Applications autililitie. all Huse

### Vector Indexes Leverage Partitions / RAC / Exadata



# **From Juan Loaiza Interview**

### <u>Time of Big Transitions</u>

- Generating Apps with GenAl
- AI & AI Search
- Dramatic! Orders of benefit at least 10x
- GenAI build directly into DB No need to be a data scientists
- Al Vector search take a document/image with the content (not pixels) build a vector for this & compare things better. Very new tech!!!
- Used to need to be a data scientist... now just <u>use SQL with vector searches</u>.
- Talk to the system like ChatGPT to pose questions to the database & get answers back using vector search (<u>in 23c only</u>)
- AI benefit does things like Generate Apps describe it & they will build the first version of it. You get a DRAFT of it. You just need to check everything (like chatGPT).
- It will keep improving! Hard to predict where it is going not as esoteric used to be for corner cases easier now & better.
- Won't replace experts gives a first draft verify draft / update it / own it
- Al won't get it 100% right
- Traditionally via Relational Data App users want to use **JSON & Graph: ALL ok now**.



Al vector search using

sophisticated vector indexes

### Search on Data with AI Vectors & Vector Indexes

Vectors are used to represent the semantic content of images, documents, videos, etc.



A vector is a sequence of numbers, called dimensions, used to capture the important "features" of the data

42

16

21

### **Oracle Vector Database**

### Example: the features for a house image could be



Each dimension represents a different feature of the house

House vectors when collapsed into 2 dimensions instead of hundreds could look like this





### **Vector Search**

Imagine a house-hunting app that helps customers find houses for sale that are similar to a picture the customer uploads

# The distance between the vectors is proportional to their semantic similarity





### Search on vector (GenAI), add prices/locations



### **Create table with Vector Data Type & Blob**

- CREATE TABLE house for sale (house id price city house photo blob, house vector vector
  - number, number, varchar2(400),

Find houses that are similar to this picture and match the customer's preferred city and budget



#### 

);

```
SELECT ....
FROM house for sale
WHERE price <= (SELECT budget FROM customer ...)
      city in (SELECT search_city FROM customer ...)
AND
ORDER BY vector distance(house vector, :input vector);
```

### **AI Vector search Preview!**



### Announcing: Al Vector Search in Oracle Database 23c

Sign up for Preview Now



### Cohere & Oracle GenAl Partnership (Signed June 2023)

- Aiden Gomez, Cohere CEO worked on "Attention is all you need" paper on Transformers Aidan while at Google Brain
- Cohere turns words to numbers with semantic knowledge
- Knowledge Augmentation Don't read 100 docs, feed into Cohere LLM models (Working with ALL Oracle Teams).
- Vector DB uses your information & knowledge that you have
- <u>Challenges</u> Hallucinations (made up "facts")
- **RAG** most promising **solution to hallucinations**
- <u>Models trained on the web can now use your own data with</u> **RAG (Retrieval Augmented Generation)**
- Training vs. RAG Training good to get model to speak in your brand voice - Adds new knowledge coming in every msec when you update the DB & RAG keeps it up to date.
- Future Embedding Models performs twice as well in speed & accuracy. Also compress 32x with 96% accuracy.
- **Noisy data** (pdf scrapes / errors); bad emails; No matter how noisy, you still get accurate results with what we're building.



**c**ohere

Officially launched partnership at Cloud World (Sept 2023)

ORACLE



### **Retrieval Augmented Generation**

**Retrieval Augmented Generation** 

How it works

The user's question is

sent to a Vector DB

encoded as a vector and

Vector Databases augment Generative AI by retrieving detailed, often private content needed to answer questions

Called: Retrieval Augmented Generation (RAG)

Vector DB finds private content that closely match the user's question



# **Oracle AI & GenAl**

### **SOTA = State of the Art**

### Coming soon: OCI Generative AI

#### State-of-the-art foundational models

We have partnered with Cohere to bring SOTA foundational models to both OCI customers and Oracle SaaS customers.

#### Fine-tuning support

Tune custom models with your own data to solve specific problems or target specific domains.

#### Fully hosted on OCI

All processing and data storage happens inside OCI, no cross-region or cross-cloud communication.

#### Respect for customer privacy

Customer training and inference data is owned by the customer and only used to serve the customer.

### PAYG and single tenant, dedicated hardware

Pay per token or host the models on dedicated hardware for stable performance.



### The Oracle Al Stack



# **Answer Detailed Questions / Supply Manuals**



### **Answer Location Questions - Integrate Map**



### **Ask Questions & Reference Document AI Searches**

#### Chat with Nicky

100

100

Welcome to Acme Insurance. How can I help you today?

Are hotel stays covered in my policy?



Ask a Question

Boarding is not covered as part of your current policy. (See Policy Exclusions, Page 15)

K Now displaying Page 13.

# FOUND ON THIS PAGE BELOW

Page 04

#### Exclusions

We will not pay for costs associated with or resulting from the following:

 Aesthetic, cosmetic, endodontic, or orthodontic dental services such as caps, crowns or crown amputation, fillings, implants and root canals or planing.

/ 21

- b. Organ or heart valve transplants.
- c. Boarding.
- d. Conditions that occur during a waiting period.
- e. Cosmetic and elective prostheses or procedures (including but not limited to claw removal, ear cropping and tail docking).
- f. Dental cleanings unless used to treat a covered illness or covered by an applicable endorsement.
- g. Experimental or investigational treatment or medication (including clinical trials) that is not generally accepted in the veterinary medical community as effective or proven.
- h. Funeral services, memorial items, urns, caskets, or burial plots/fees.
- Grooming or grooming supplies (including but not limited to non-prescription baths, ear cleanings, non-prescription shampoos and nall trims).
- . Food products.
- k. House call fees, time and travel expenses to and from the veterinarian's premises or hospital.
- Illness or injury that results from intentional, malicious, or grossly negligent activities or from failure to perform actions commonly accepted as responsible pet care by you, a member of your household or a caregiver for your pet.
- m. Ligament and knee conditions, if any ligament and knee condition occurred prior to the first effective date of the applicable coverage or during a waiting period.
- n. Non-medical supplies such as but not limited to toys, leashes, ramps, bedding or other devices intended to prevent injury or illness, but that do not treat a condition.
- Non-veterinary services (including but not limited to administrative fees, medical records expenses, medical waste, discount package or membership fees, postage and tax).
- p. Pre-existing conditions that occurred on or before the first effective date of the applicable coverage or during a waiting period.

### Stanford (113 authors / 215 pgs.) on Foundation Models 2021/2022

#### On the Opportunities and Risks of Foundation Models

Rishi Bommasani\* Drew A. Hudson Ehsan Adeli Russ Altman Simran Arora Sydney von Arx Michael S. Bernstein Jeannette Bohg Antoine Bosselut Emma Brunskill Erik Brynjolfsson Shyamal Buch Dallas Card Rodrigo Castellon Niladri Chatterji Annie Chen Kathleen Creel Jared Quincy Davis Dorottya Demszky Chris Donahue Moussa Doumbouva Esin Durmus Stefano Ermon John Etchemendy Kawin Ethavarajh Li Fei-Fei Chelsea Finn Trevor Gale Lauren Gillespie Karan Goel Noah Goodman Shelby Grossman Neel Guha Tatsunori Hashimoto Peter Henderson John Hewitt Daniel E. Ho Jenny Hong Kyle Hsu Jing Huang Thomas Icard Saahil Jain Dan Jurafsky Pratyusha Kalluri Siddharth Karamcheti Geoff Keeling Fereshte Khani Omar Khattab Pang Wei Koh Mark Krass Ranjay Krishna Rohith Kuditipudi Ananya Kumar Faisal Ladhak Mina Lee Tony Lee Jure Leskovec Isabelle Levent Xiang Lisa Li Xuechen Li Tengyu Ma Ali Malik Christopher D. Manning Suvir Mirchandani Eric Mitchell Zanele Munvikwa Surai Nair Avanika Naravan Deepak Naravanan Ben Newman Allen Nie Juan Carlos Niebles Hamed Nilforoshan Julian Nyarko Giray Ogut Laurel Orr Isabel Papadimitriou Joon Sung Park Chris Piech Eva Portelance Christopher Potts Aditi Raghunathan Rob Reich Hongyu Ren Frieda Rong Yusuf Roohani Camilo Ruiz Jack Ryan Christopher Ré Dorsa Sadigh Shiori Sagawa Keshav Santhanam Andy Shih Krishnan Srinivasan Alex Tamkin Rohan Taori Armin W. Thomas Florian Tramèr Rose E. Wang William Wang Bohan Wu Jiajun Wu Yuhuai Wu Sang Michael Xie Michihiro Yasunaga Jiaxuan You Matei Zaharia Michael Zhang Tianyi Zhang Xikun Zhang Yuhui Zhang Lucia Zheng Kaitlyn Zhou Percy Liang\*1

#### Center for Research on Foundation Models (CRFM) Stanford Institute for Human-Centered Artificial Intelligence (HAI) Stanford University

AI is undergoing a paradigm shift with the rise of models (e.g., BERT, DALL-E, GPT-3) trained on broad data (generally using self-supervision at scale) that can be adapted to a wide range of downstream tasks. We call these models foundation models to underscore their critically central yet incomplete character. This report provides a thorough account of the opportunities and risks of foundation models, ranging 

 Machine Learning
 Deep 3
 Foundation Models

 Emergence of...
 "how"
 Features
 Functionalities

 Homogenization of...
 learning algorithms
 architectures
 models

Fig. 1. The story of AI has been one of increasing *emergence* and *homogenization*. With the introduction of machine learning, *how* a task is performed emerges (is inferred automatically) from examples; with deep learning, the high-level features used for prediction emerge; and with foundation models, even advanced functionalities such as in-context learning emerge. At the same time, machine learning homogenizes learning algorithms (e.g., logistic regression), deep learning homogenizes model architectures (e.g., Convolutional Neural Networks), and foundation models homogenizes the model itself (e.g., GPT-3).



# **From Stanford Paper**

- Machine learning: Most AI systems today are powered by machine learning, where predictive models are trained on historical data and used to make future predictions.
- **Deep neural networks** would be <u>trained on the raw inputs (e.g., pixels</u>), and <u>higher-level features would emerge through training</u> (a process dubbed "representation learning").
- Foundation models are enabled by transfer learning [Thrun 1998] and scale. The idea of transfer learning is to take the "knowledge" learned from one task (e.g., object recognition in images) and apply it to another task (e.g., activity recognition in videos).

Fig. 1. The story of AI has been one of increasing *emergence* and *homogenization*. With the introduction of <u>machine learning</u>, *how* a task is performed emerges (is inferred automatically) from examples; <u>with deep</u> <u>learning</u>, the high-level features used for prediction emerge; and with foundation models, even advanced <u>functionalities such as in-context learning emerge</u>. At the same time, machine learning homogenizes learning algorithms (e.g., logistic regression), deep learning homogenizes model architectures (e.g., Convolutional Neural Networks), and foundation models homogenizes the model itself (e.g., GPT-3).

### **From Stanford Paper**

...

**One Model** 

A finite number of generalizable model

mechanisms are combined to produce

output

word

letter

behaviors across tasks.

numbe

124



Fig. 23. The one model-many model nature of foundation models: A central interpretability question is to understand where a foundation model lies on the spectrum between *one model* and *many models*. As one model, behavior can be made interpretable by identifying and characterising the finite number of generalizable model mechanisms used to produce behaviors across tasks (e.g., mechanisms that assign meaning to words, compare quantities, and perform arithmetic). As many models, explanations of model behavior in one task are not necessarily informative about behavior in other tasks, thus requiring the independent study of behavior in each task.

Will Businesses of the Future just be a Single Foundation Model to do all Tasks? *(my own question)* 

# From Stanford Paper (Example Application)

### Section on Healthcare & Biomedicine



# **Better World – Leverage Tech!**

### Steve Wozniak on AI: Will we be pets or mere ants to be squashed our robot overlords?

Apple co-founder Steve Wozniak predicts a 'scary' future when artificial intelligence takes



# Robots We Grew up With...



### Movie Robots... Closer to the Future

/\* MORAVEC PARADOX: WHAT'S EASY FOR MACHINES IS DIFFICULT FOR HUMANS AND WHAT'S EASY FOR HUMANS IS DIFFICULT FOR MACHINES: E.G. IT'S HARD TO BUILD A ROBOT WITH THE SENSORIMOTOR SKILLS OF A 1 YEAR OLD HUMAN



Moravec's Paradox

MIT MANAGEMEN



Logical thought is hard for humans and easy for computers, but picking a screw from a box of screws is an unsolved problem.

### **Actual Robots Now... Beyond Science Fiction**



## Mirror Image













### Mirror Image





Prof. Hiroshi Ishiguro, right, inspects his robotic twin, Geminoid HI-1, also known as 'Gemmy,' who handles his teaching duties at Osaka University in Japan. Photo courtesy of ATR Intelligent Robotics and Communication Laboratories.











### GenAl inside APEX, Sensors, Robots...etc.

Transformative Technologies: Applied to other Industries

- Generative Artificial Intelligence
  - APEX No Code Application Generation System
  - Autonomous Database Stores Vast Amounts Al Training Data
- Internet of Things: Sensors & Robots
  - Sensors Collect Vast Amounts of Training Data
  - Robots Lower Costs and Improve Product Quality & Job Quality



### **Use Oracle Virtual Assistant with Robots**



### **Oracle Virtual Assistant Interface**

		Dashboard Analysis	
Now	Updated every	i0 secs Intents Upr	dated every 30 secs
2	3 issues 1	2% A 332 Published	
Conversations	4 Average Exchanges	Total 16 Not Published	
This Week 🔹 April 8, 20	18 to April 14, 2018	125 Conversations	405 66 Exchanges Issues
Most Popular Expression	s 🕜 🔲 Without Issues 📕 With	Issues Most Popular Intents 🕢 Sort By Total 🔳 Without Issues	With Issues
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Issues 🕢		There san a find the making a hea	

## Leveraging – DB, Al & Virtual Reality!



### Virtual Reality



- > Immersion in virtual worlds
- > Total interaction with virtual
- > E.g. Oculus Rift

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Mixed Reality



- > Virtual World integrated to reality
- > Interaction between reality and virtual
- > E.g. Microsoft HoloLens



Augmented Reality



- > Virtual on top of reality
- 2 Limited interaction with the virtual

digital intelligence 138

> E.g. Smartphones & tablets

actimage

# What Is XR (Extended Reality)?

#### XR describes virtual, augmented, and mixed-reality technologies





### A World of Difference (Getting Closer)



### Future Tech is in AI:

### You can Leverage this NOW!







### The After Hours (Future Sentience Issues Ahead)



### The Digital Transformation Ahead

### Digital Transformation 2000 to 2050 A historically significant change in humanity...







Wearing Digital

Implanting Digital The Hive Mind

### **Connection to the Brain – Currently Working**



C Johns Hopkins University
# Walking Distance (Create your past to view)









Developer Creates VR Time Machine To Relive His Past Year

July 13, 2020 - by Bobby Carlton







# Digital – How did we go from Magical to Toxic?



Gerd





Oracle Database 12c 12c **Release 2 Performance Tuning Tips and Techniques** 

## Fully Encrypted Database **Tablespace Encryption (TDE)**

## Oracle Database Security Built over MANY years...

Government customer

Oracle Audit Vault DB Security Evaluation #19 Transparent Data Encryption EM Configuration Scanning Fine Grained Auditing (9i) Secure application roles Client Identifier / Identity propagation Oracle Label Security (2000) Proxy authentication Enterprise User Security Global roles Virtual Private Database (8i) Database Encryption API Strong authentication (PKI, Kerberos, RADIUS) Native Network Encryption (Oracle7) Database Auditing

Encryption in the Silicon (M7) **Oracle Multi-Tenant Security (PDBs)** 

**Oracle Database Vault** 

ORACLE<sup>®</sup> 19 Database

18c: User-defined Master Encryption Key (bring your own key - software keystores)

**19c:** Oracle Database supplied schema-only accounts have passwords removed (not sample accounts)



18c

Oracle

Database

Global Fault-Tolerant Key Vault & Oracle Data Safe



In-Database SQL Firewall blocks unauthorized SQL & SQL Injection Attacks



## Gartner Hype Cycle August 2018 All about Tech Creating a New Reality



COOK CLAPSON MICH



States Country in

## What's comes *after* the Exadata Zone? YOU will soon be in for more...

	Directly Addressable	Indirect/E
<u> 4 Bit:</u>	16	(640)
8 Bit:	256	(65,536)
16 Bit:	65,536	(1,048,57
32 Bit:	4,294,967,296	<b>x</b>
64 Bit:	18,446,744,073,709,551,616	
128 Bit:	3.4 x 10e+38 quantum leap!	

xtended 6)



- Qubits allow multiple states so that you can look at all of the possibilities/probabilities at one time (IBM **Q** is 20 qubits).
  - The "Quantum Zone" next (Quantum Physics is incomplete Einstein)
    - Just 512 qubits would store 512-bits of addressable memory or  $2^{512}$  (which is well over a googol or 1 with 100 zero's after it **a googol is about 2^{332}**).
    - Brush up on your Eigenvectors, Eigenvalues, Pauli Matrices & Grover's Algorithm
    - Create Singularity ... all atoms of a person by 2045 (I think earlier); 12-Monkeys •
    - Private universes Is there one for each person? (Schroeder's cat I think not) •
    - Rearranging atoms to create new objects; Nanotech + Quantum Physics coming!

# **Quantum Computing makes ML Fast Enough!**

**Google:** 47 years to 6 seconds 241M times faster than 2019's





## Gartner 2021 hype cycle for Emerging Tech

## Hype Cycle for Emerging Technologies, 2021



# 3 Types of Artificial Intelligence

#### Artificial Narrow Intelligence (ANI)



Stage-1

#### Machine Learning

 Specialises in one area and solves one problem







#### Artificial General Intelligence (AGI)



Stage-2

#### Machine Intelligence

 Refers to a computer that is as smart as a human across the board

> 2023: You're Here

#### Artificial Super Intelligence (ASI)



Stage-3

#### Machine Consciousness

 An intellect that is much smarter than the best human brains in practically every field

## Final Thoughts... world changing fast!

"Those who use things of the world should not become attached to them. For the world in its present form is passing away."

1 Corinthians 7:31



# **Star Trek**

- <u>Communicator</u> Motorola Flip Phone
- Phaser EPM or Stun Gun / Taser
- <u>Tablets (Medical)</u> Tablet Computers
- <u>Tricorders</u> Many Medical Devices (below)
- <u>Translators</u> Google Translate (others)
- <u>Tractor Beam</u> MIT has it in concept
- <u>Telepresence</u> Zoom Virtual Conferences
- <u>Geordi's Visor</u> Robotic Eyes / Implants
- <u>Communicator Badges</u> Many Security Badges
- Food Replicator 3D Printer
- <u>Holodeck</u> VR
- <u>Teleportation</u> Quantum Entanglement
- Big Screen TV Everyone has it
- Hands Free Phone Bluetooth headset / Airpods

















## Hololens VR Apps Above



Microsoft working on Holodeck



# The Digital Transformation Ahead

## Digital Transformation 2000 to 2050 A historically significant change in humanity...







Wearing 1 Digital

Implanting Digital

The Hive Mind

## World now changing Faster! The Singularity: Humans Transcend Biology

WHEN HUMANS TRANSCEND BIOLOGY



## Quantum Entanglement

"Spooky action-at-a-distance" (A. Einstein)





SINGULARITY IS

ТНЕ

NEAR

## RAY KURZWEIL

Brain implant controls robotic arm - with the power of thought

Breakthrough as neuro-prosthetic device implanted in "higher" brain region, allows paralysed man to control robotic arm just by thinking about it



• A summe-prostitutic device implanted in Enili Sorta's boars allowed live to donk unaided for the last time in ten on "Phytography-Spence Kells and Christian Klaey/Calteria

# Summary – Apply Technology & W.I.N.

- Economic Potential of GenAl
- **Economic Impact of Robots**
- □ ML & Oracle Overview & ADB
- Oracle Generative AI Coming
- □ Transformers, ChatGPT & Foundation Models
- □ Oracle Vector DB, GenAl, & Cohere

Machine Learning Future, Robots & VR

richniemiec@qmail.com

viscosityna.com

@richniemiec







# Black Mirror out Dec. 2011- Dystopian

• **Nosedive:** (Social Meeting Addiction & Ratings)

• Hated in the Nation (Cancel Culture)





• Be Right Back (ETER9)



- The Entire History of You
  (Kapture / Google Glass / Google Clips)
- Metalhead (Robot Dog)







# **A Thing About Machines - People Frustrated**













HAVE U TRIED TURNING IT OFF AND ON AGAIN?







# Final Thoughts... Catch your Ride!



*"Things may come to those who wait, but only the things left by those who hustle."* — Abraham Lincoln



## Oracle never caught from behind Oracle's 46<sup>th</sup> Anniversary in 2023

- Great Sales/Marketing
- Great Database
- Applications Leader
- BI Leader
- In the lead except Cloud
- GAME OVER
- Hardware/Software Engineering!
- Have Everything to Win in Cloud + Al!

In Memory of Ken Jacobs, Dr. DBA & Joel Kallman





Joel R. Kallman

1966-2021

hief Innovation Officer, Viscosity North America

Dr. DBA, Ken Jacobs, He will be missed!! Oracle's best advocate of User Groups; Kind, Giving, Positive, Honest, Humble & Smartest Guy in the Room! Sadly, Ken suffered a pulmonary embolism and passed away last Friday at the age c ...see more

#### Who is the Dr. pictured below?



Dr. DBA - Ken Jacobs (in the middle)

🚫 😂 💟 104 · 43 comments

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Our services give you the training you need so your Oracle database runs faster and more efficiently. And, you get the credit!



## References



- The Emerging Technology Roadmap, Scott Klososky
- Futurist Gerd Leonhard The Futures Agency, Technology vs. Humanity, Gerd Leonhard, oracle.com & Juan Loaiza / Doug Hood presentations, amazon.com, smartcitiescouncil.com, youtube.com, business coach, libelium.com, monetate, en.wikipedia.org, Netflix, Black Mirror, hometoys.com, FPOV, huffingtonpost.com, thegardian.com, nationalgeographic.com, newscientist.com, enswmu.blogspot.com, dailymail.co.uk, FutureRobot, theguardian.com, thinkhealthwireless.blogspot.com, ge.com, cmswire.com, runningsupplement.co.uk, guickmeme.com, nike.com, thisiswhyimbroke.com, businessinsider.com, slideshare.com, forrester.com, spiceworks.com, mwaintel.com, humancapitalist.com, wired.com and Wired Magazine, shodanhq.com, developer.nokia.com, extremetech.com, Getty Images, Dr. Quantum, Leo Kouwenhoven, Telecom Tech News, BBC Radio, Actimage, MIT & any other company products are the property of their respective companies.



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- References include Rich Niemiec's Exadata Presentation & Oracle 12cR2
  Database Performance Tuning Tips & Techniques book, <u>www.oracle.com</u>, en.wikipedia.org, slashgear.com, gifsoup.com, <u>www.amazon.com</u>, Tech
   Crunch, <u>www.rolta.com</u>, The Twilight Zone, Information Week, Gartner,
   Computerworld, Quest, Data and Technology Today, Forbes, Quest,
   Orbit, Computer Weekly, Redmond, Database Trends & Applications,
   dsp, Dataversity, zdnet, DBVisit, Steve Jones, Kerry Osborne, Julian
   Dontcheff, Accenture, Quora, Brent Ozar, & Oracle OpenWorld





## Getting Started—Oracle ML/AI Resources

**Oracle Advanced Analytics Overview Information** 

ORACLE'

•	Oracle Machine Learning Newest Features and Road Map.pptx presentation	
•	Blog post: Simple Guide to Oracle's Machine Learning and Advanced Analytics	
•	Oracle Advanced Analytics Public Customer References	
•	Oracle's Machine Learning and Advanced Analytics Data Management Platform	<u>s</u> white paper on OTN
	YouTube recorded Oracle Advanced Analytics Presentations and Demos,	White Papers
•	Oracle's Machine Learning & Advanced Analytics 12.2 & Oracle Data Miner 4.2	New Features You lube video
•	Library of YouTube Movies on Oracle Advanced Analytics, Data Mining, Machine	<u>e Learning (7+ "live" Demos</u>
	e.g. Oracle Data Miner 4.0 New Features, Retail, Fraud, Loyalty, Overview, etc.	)
ORACLE	Overview YouTube video of Oracle's Advanced Analytics and Machine Learning	
UNIVERSITY	Getting Started/Training/Tutorials	
• (	DAA/Oracle Data Miner Workflow GUI Online (free) Tutorial Series on OTN	
• (	DAA/Oracle R Enterprise (free) Tutorial Series on OTN	
• ]	ry the Oracle Cloud Now!	ou Tube Search
• (	Getting Started w/ ODM blog entry	
• <u>N</u>	lew OAA/Oracle Data Mining 2-Day Instructor Led Oracle University course	N 🐺
• (	Dracle Data Mining Sample Code Examples	Oracle's Machine Learning
ORACLE	Additional Resources Documentation & OTN Discussion Foru	Release 12.2 and
	Oracle Advanced Analytics Ontion on OTN nage	Oracle Data Miner 4.2 New Fe
	OAA/Oracle Data Mining on OTN page ODM Documentation	
	OAA/Oracle R Enterprise page on OTN page, ORE Docume	Charlie Berger, MS Engineering, MBA Digital Tr
	Oracle SOL based Basic Statistical functions on OTN	
	Oracle R Advanced Analytics for Hadoon (ORAAH) on OTN	www.twitter.com/CharlieDataMine

Oracle R Advanced Analytics for Hadoop (ORAAH) on OTN

#### Analytics and Data Summit, All Analytics, All Data, No Nonsense.

March 12-14 2010 Redwood Shores CA



## Rich's Overview *@*richniemiec

- Chief Innovation Officer, Viscosity North America: rich.niemiec@viscosityna.com
- Former CEO of TUSC
  - Inc. 500 Company (Fastest Growing 500 Private Companies)
  - 10 Offices in the United States (U.S.); Based in Chicago
  - Oracle Advantage Partner in Tech & Applications
- Former President Rolta TUSC & President Rolta EICT International
- Author (5 Oracle Best Sellers #1 Oracle Tuning Book for over a Decade):
  - Oracle Performing Tips & Techniques (Covers Oracle7 & 8i)
  - Oracle9i Performance Tips & Techniques
  - Oracle Database 10g Performance Tips & Techniques
  - Oracle Database 11g Performance Tips & Techniques
  - Quick Start Guide to Oracle Query Tuning (2015)
  - Oracle Database 12cR2 Performance Tips & Techniques
- Former President of the International Oracle Users Group
- IOUG Top Speaker in 1991, 1994, 1997, 2001, 2006, 2007
- MOUG Current President & Top Speaker Twelve Times
- National Trio Achiever award 2006
- Oracle Certified Master & Oracle Ace Director
- Chris Wooldridge Award 1998, 2012
- Chicago Entrepreneur Hall of Fame 1998
- MIT Machine Learning & AI
- Purdue Outstanding Electrical & Computer and Engineer Alumni 2007
- Board Member TEC, Entrigna, Ask DB Experts
- E&Y Entrepreneur of Year & National Hall of Fame 2001







Richard Niemiec Oracle Certified Master, Oracle ACE Directo Oracle Press

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Quick Start Guide to Oracle Query Tuning:

ORACLE

Tips for DBAs and

Developers

Rich Niemice Orsk Confed Matter State All Deale ACE Director

## **Quick FREE notes**

# Send email to (for slides): hello@viscosityna.com

(richniemiec@gmail.com)

# @richniemiec - twitter







# **Rich Niemiec**

Chief Innovation Officer at Viscosity North America

## Understand & Where to use AI & Machine Learning 101



Conf42 DevSecOps 2023 Thursday • November 30th • 5PM GMT

