

From ML Prediction to AI Decisioning

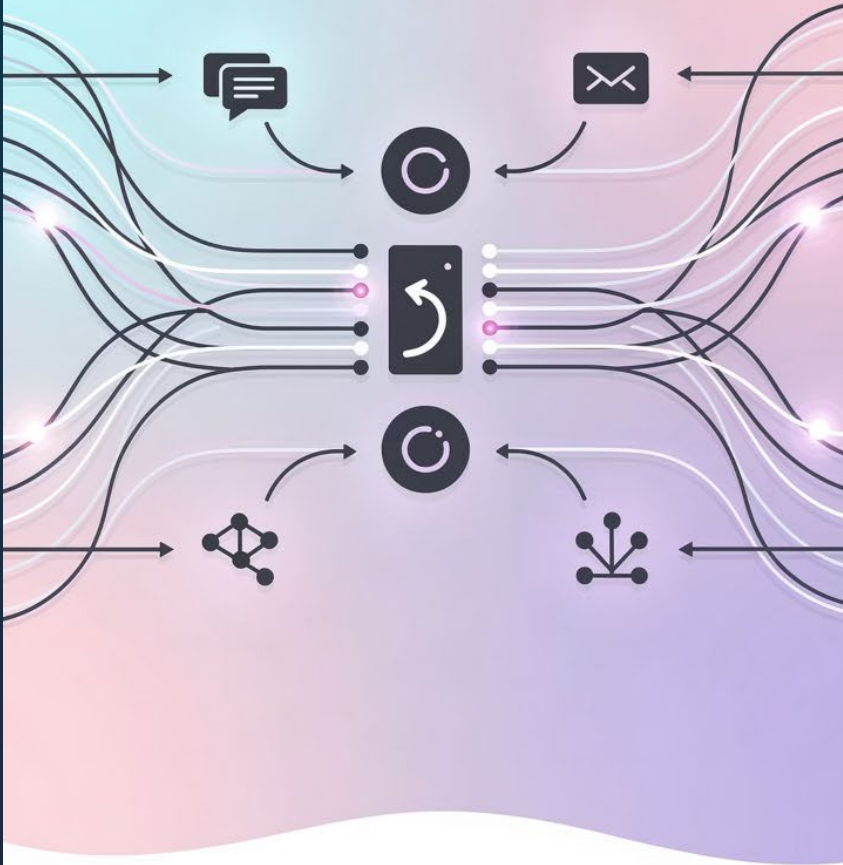
Reimagining Send Time Optimization for Modern Journey Orchestration



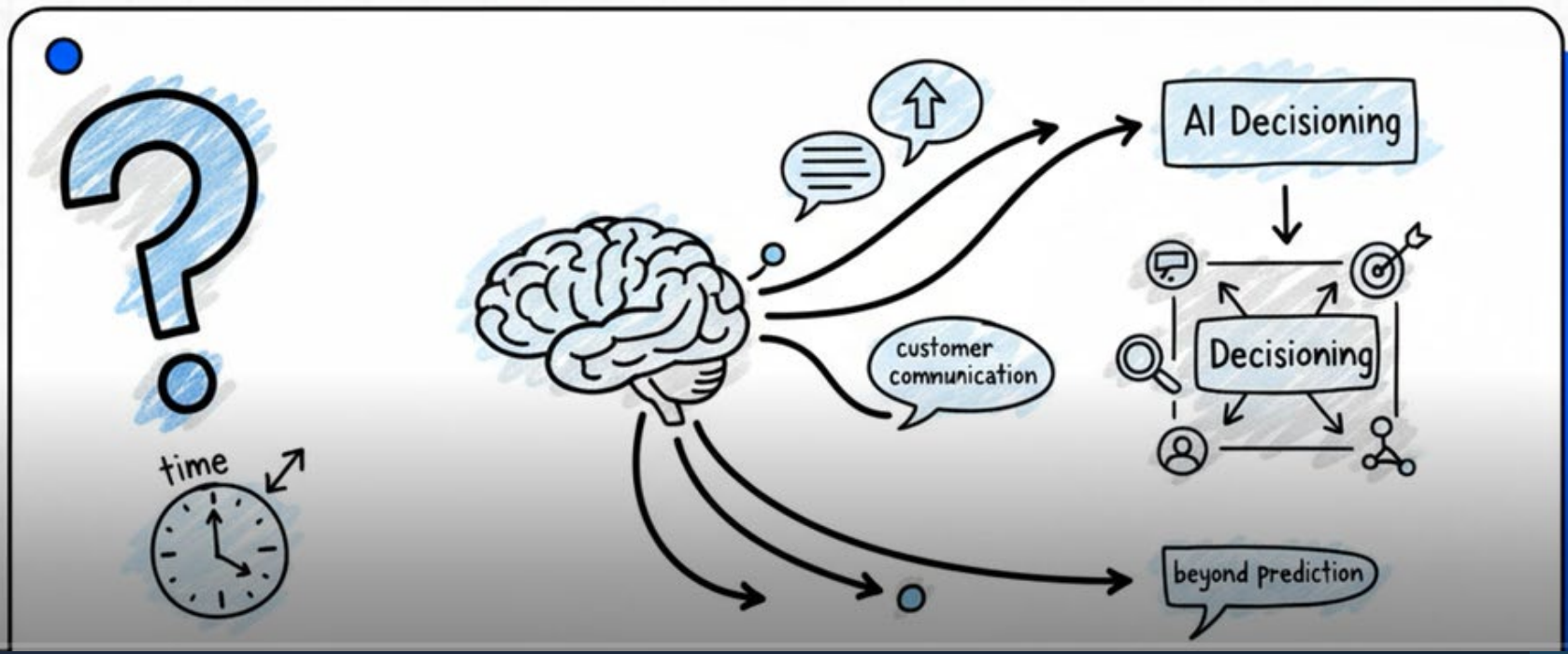
Chakravarthy Kalva
Product Manager - Adobe

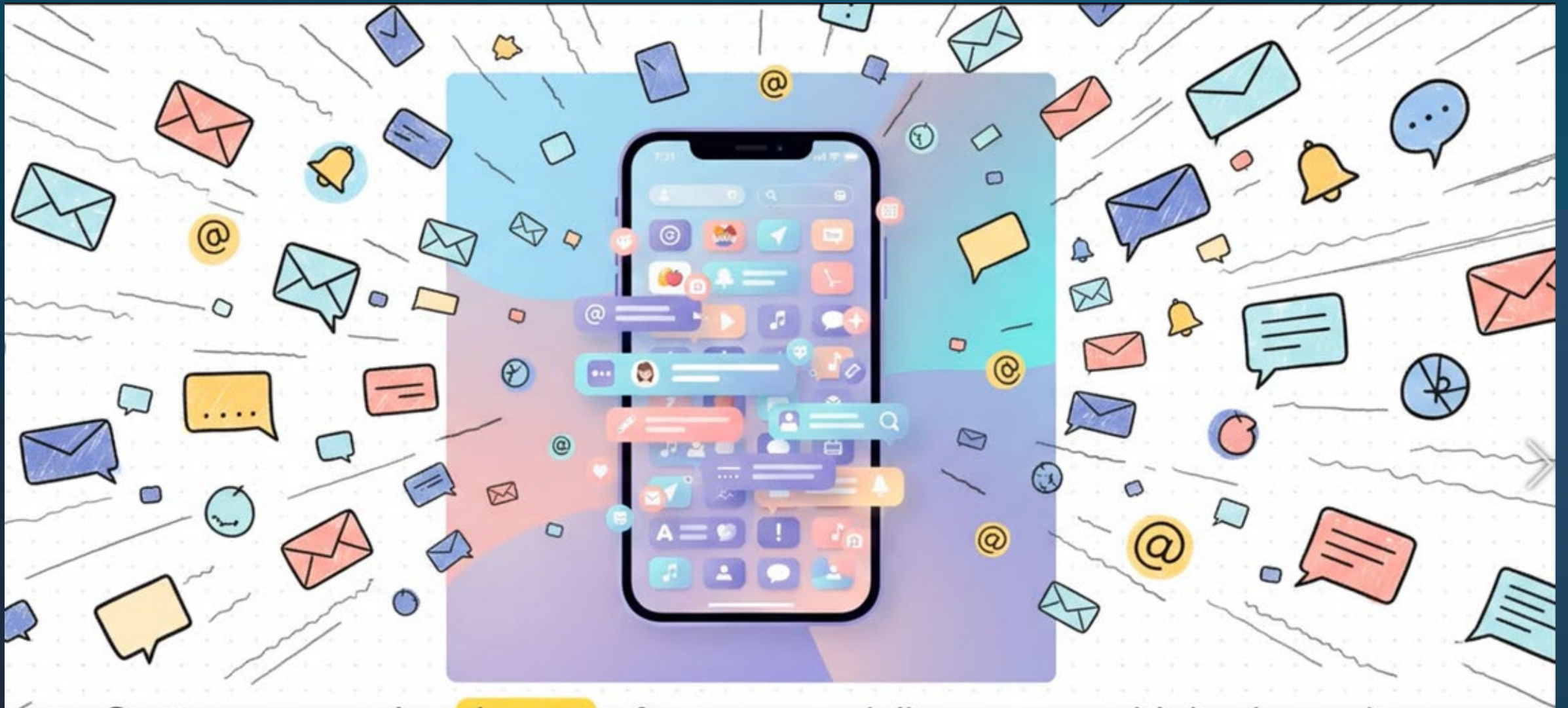


Murthy Chandrapaty
Principal Engineer- Adobe



From ML to AI Decisioning





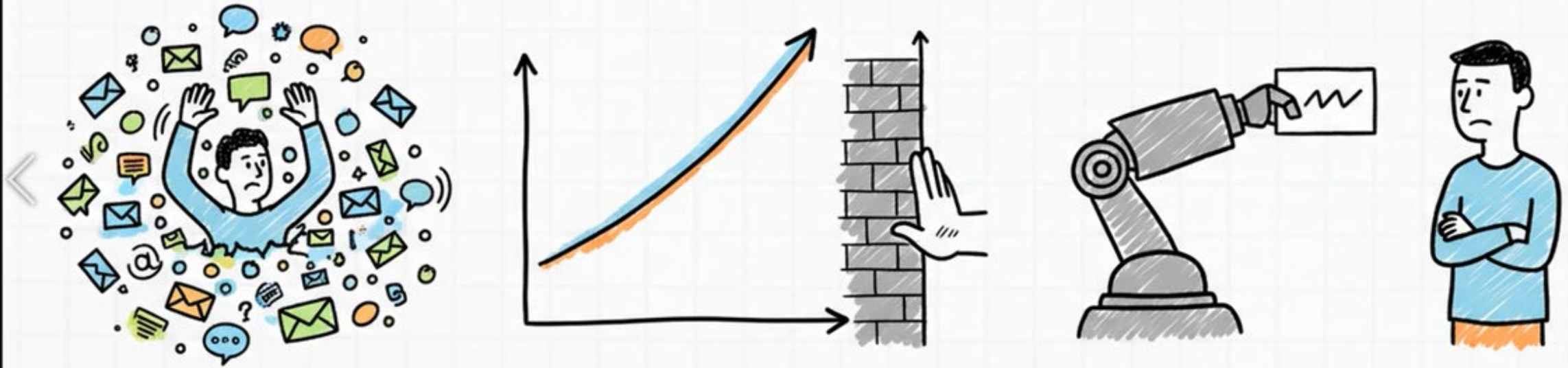
Customers receive **dozens** of messages daily across multiple channels.



If we keep sending at
the **perfect** time, why
are customers **tuning**
out?



Consequences of Overload





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The Promise of Prediction

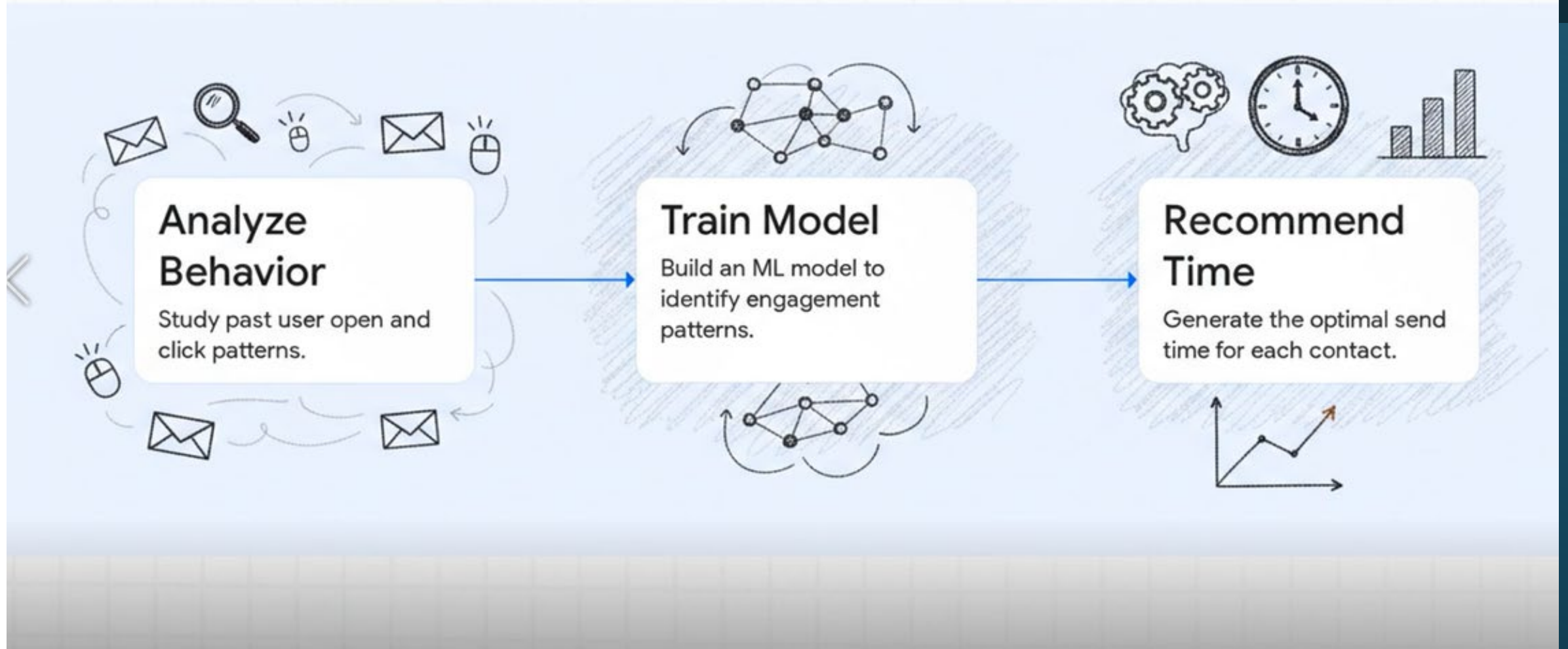
How STO Began

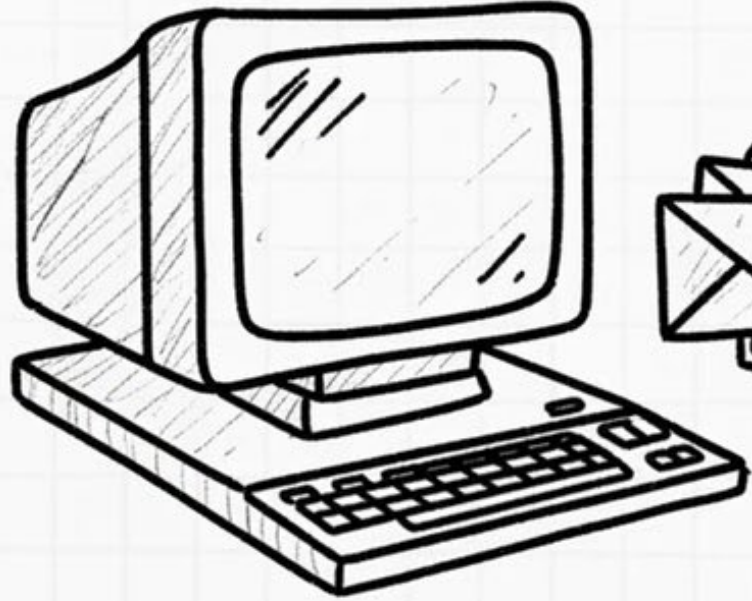


Send Time Optimization (STO)

Using historical data & ML to predict the best time to send a message to maximize engagement.

The Original STO Process





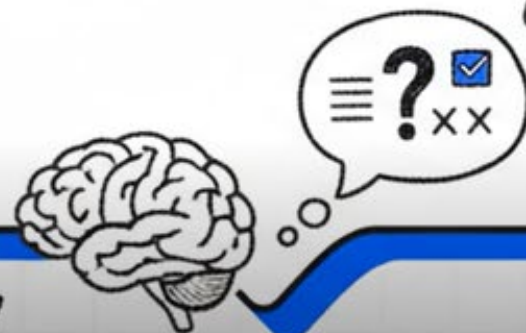


When Prediction Breaks

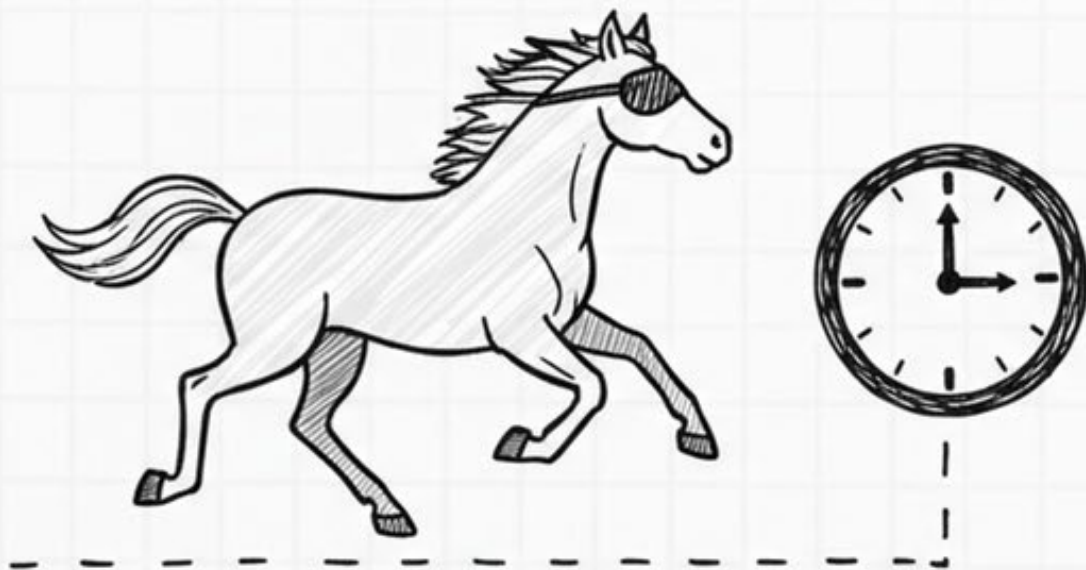
The Limits of ML



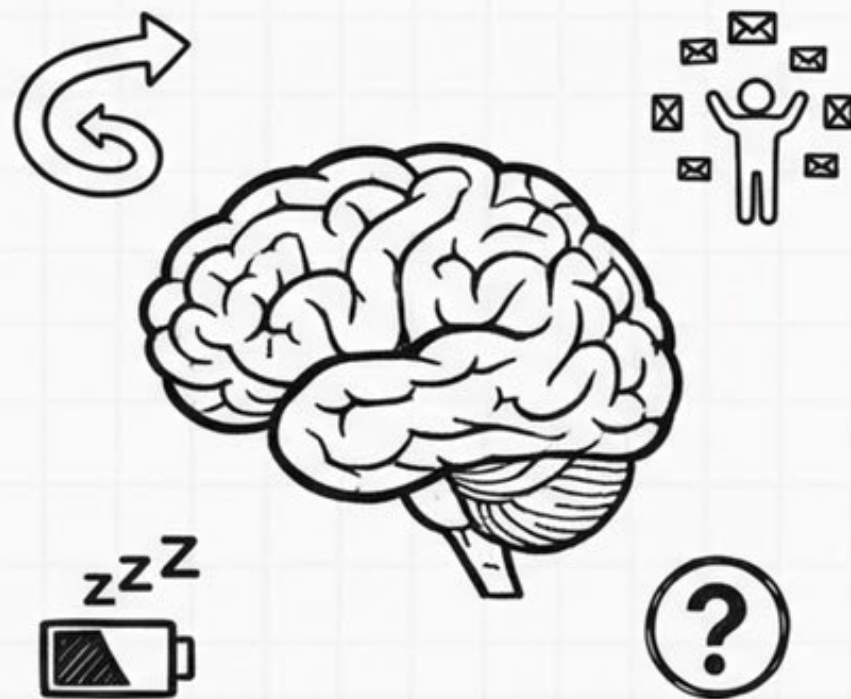
“High **probability** does not equal high **wisdom**.”



Prediction



Decision

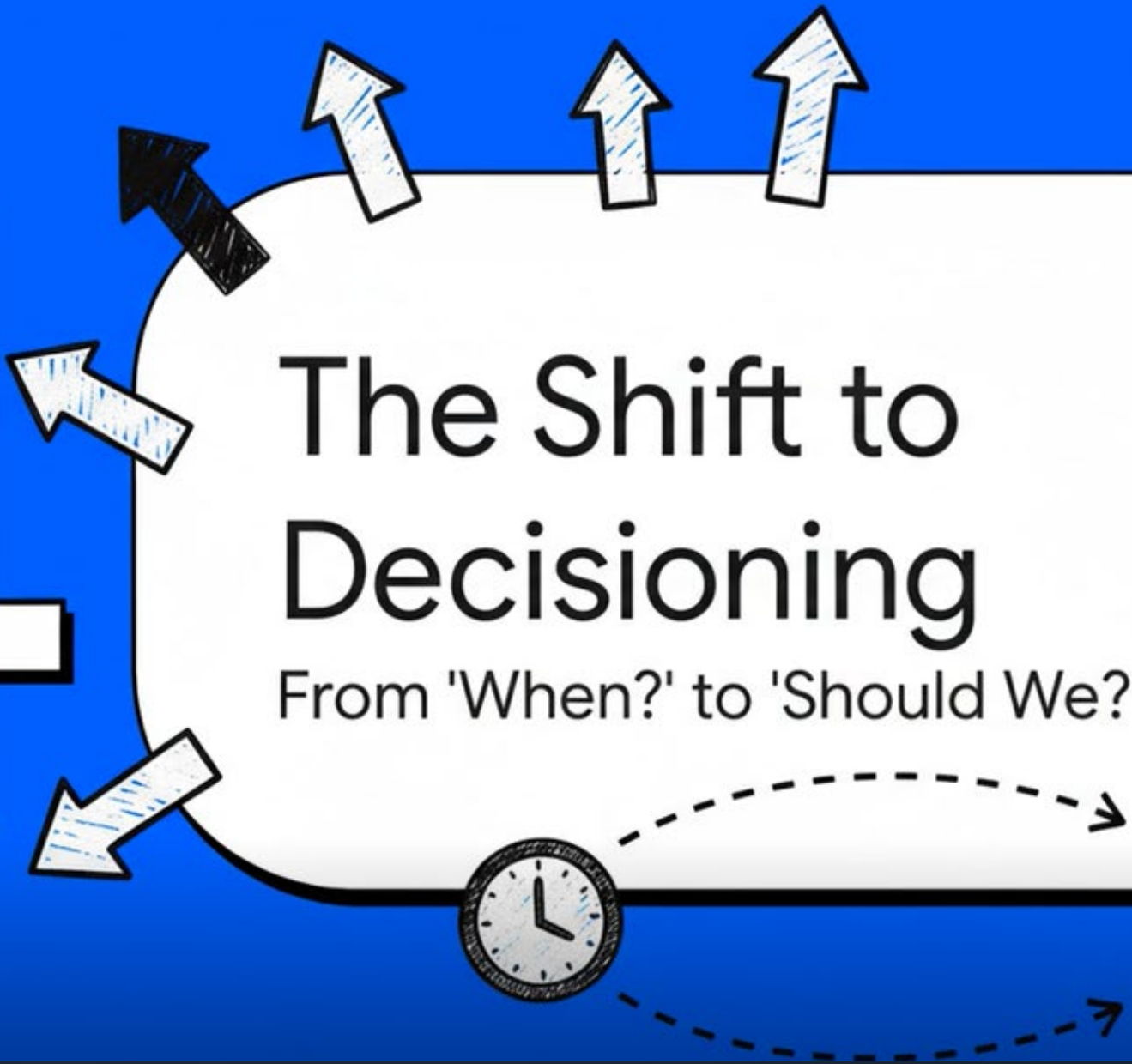




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The Shift to Decisioning

From 'When?' to 'Should We?'





ML-Based STO (Prediction)

Asks: What time is best?

Static predictions

Single signal analysis

Optimizes for open rate

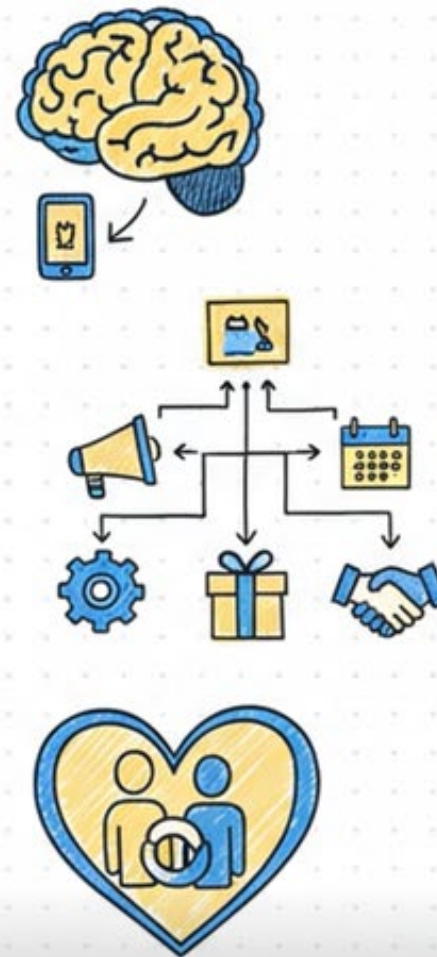
AI-Based STO (Decisioning)

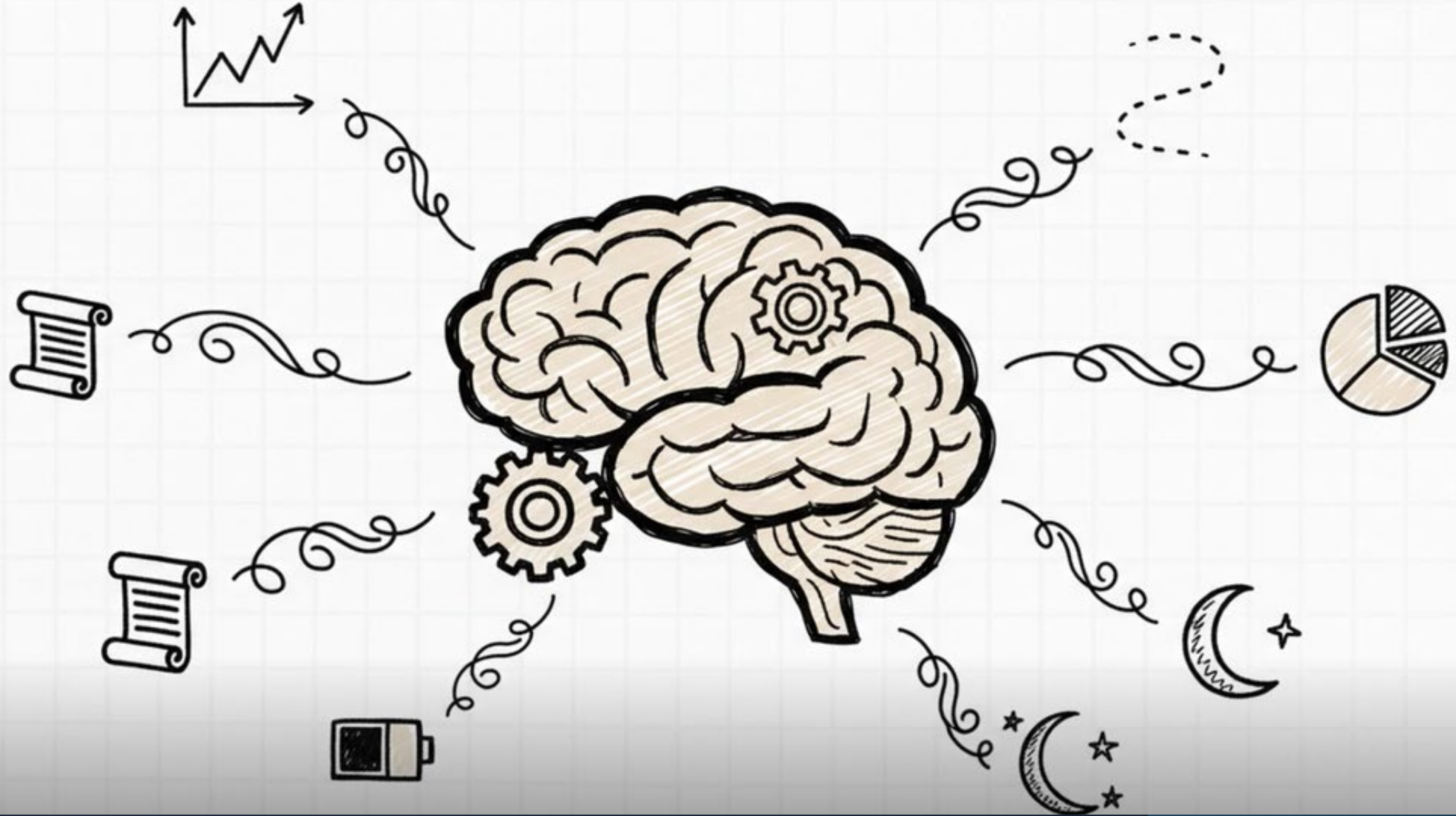
Asks: What is the best action?

Context-aware decisions

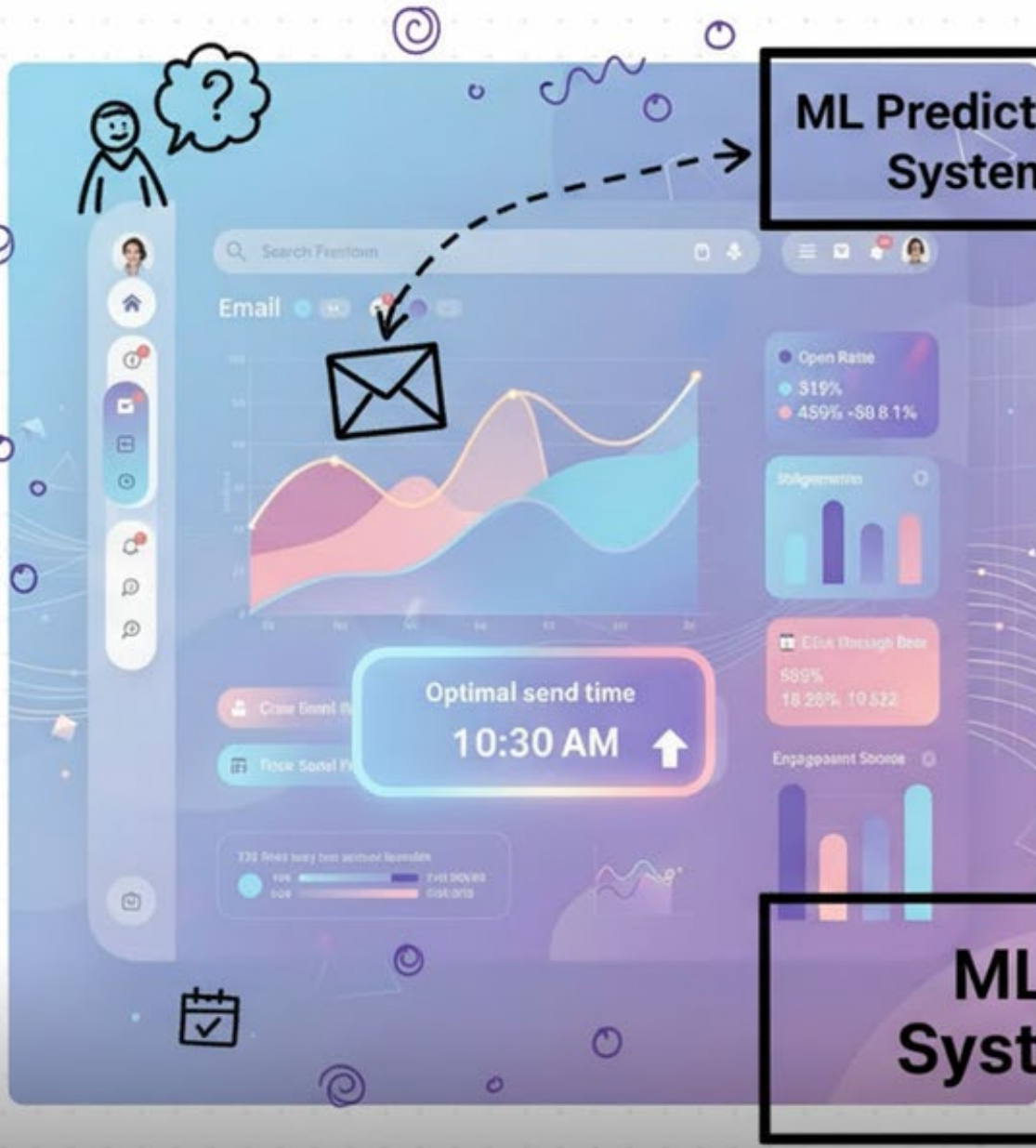
Multi-signal reasoning

Optimizes for relationship





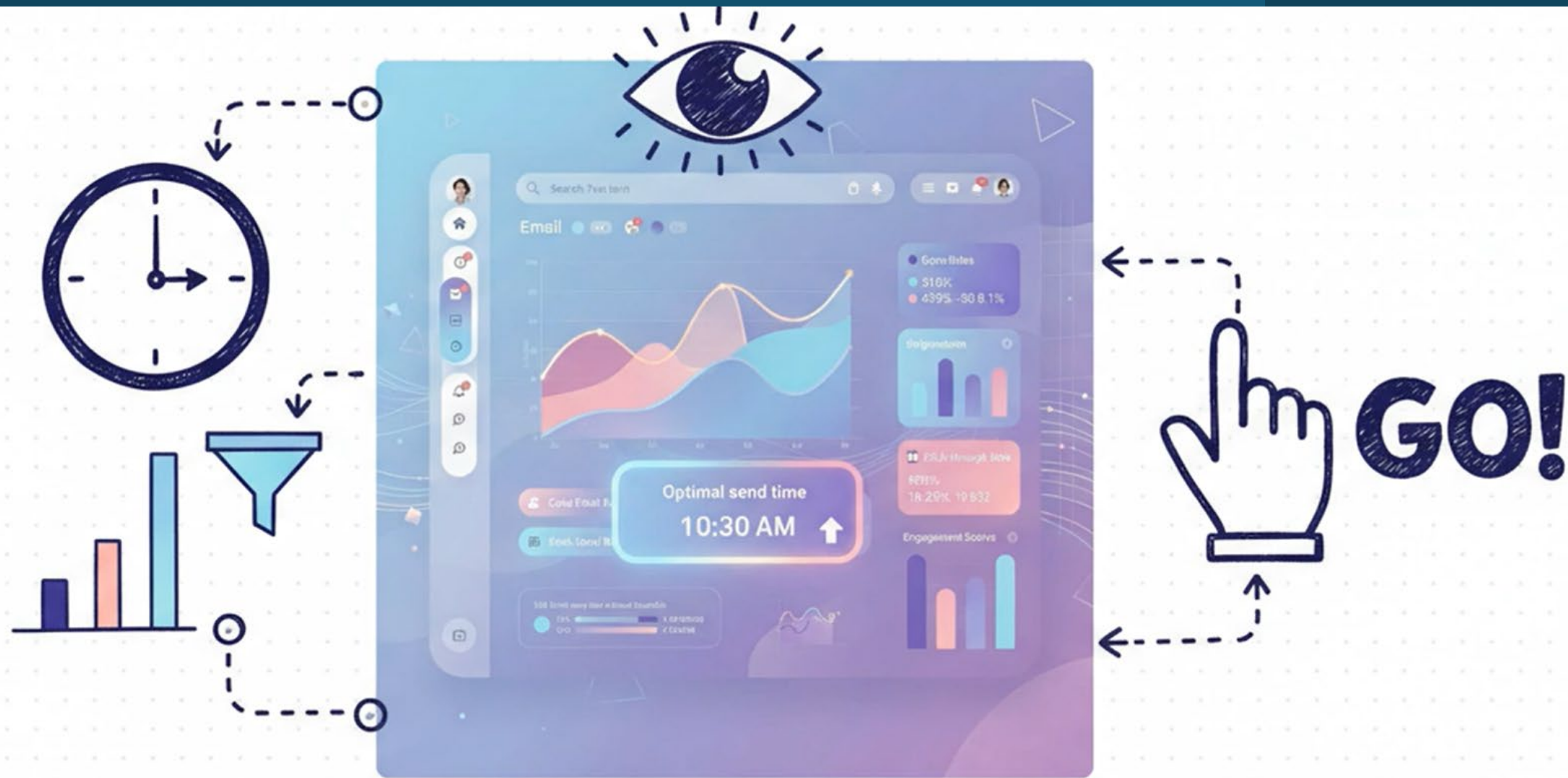
ML Prediction System



ML System



Context-Aware AI Decisioning System



ML Prediction says: **Send now**. It sees the highest historical probability of an open.



10:30 AM

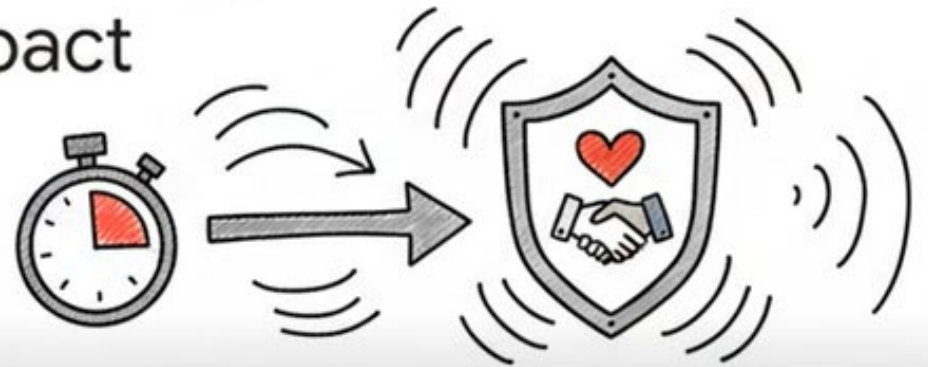


AI Decisioning says: **Hold**. It sees the customer is near their fatigue limit.



From Timing to Trust

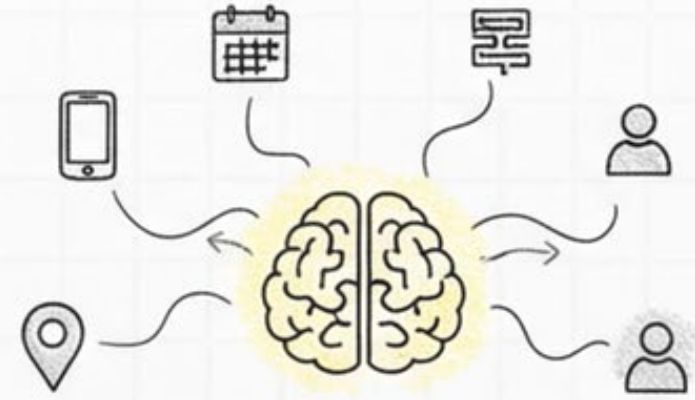
The Business Impact



Long-Term Business Impact



The Evolution of Smart Messaging



Past

Rule-Based Timing: Manual time windows and basic segmentation.



Present

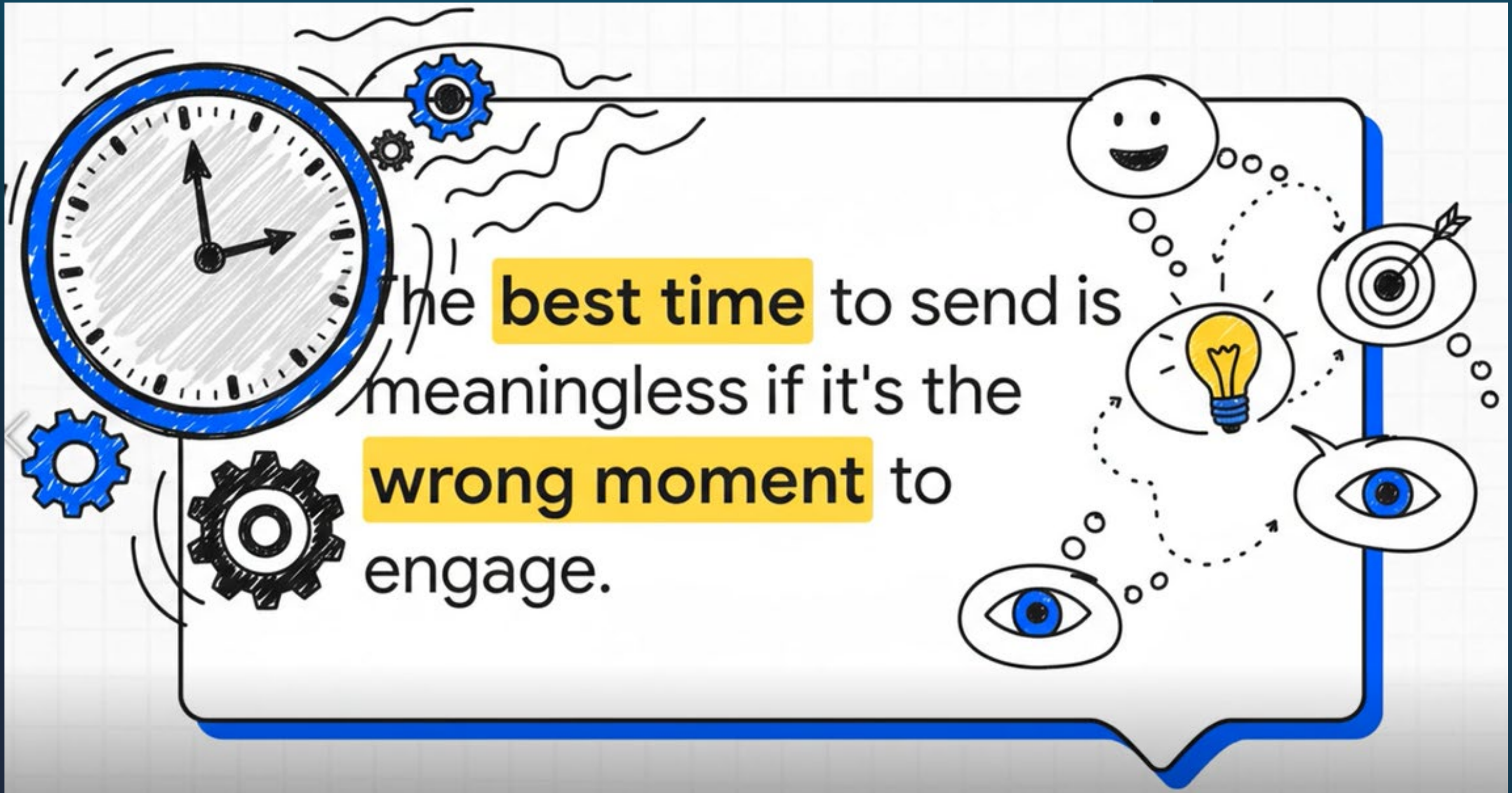
ML-Based Prediction: Predictive models using historical patterns.



Future

AI-Based Decisioning: Context-aware, intelligent orchestration.

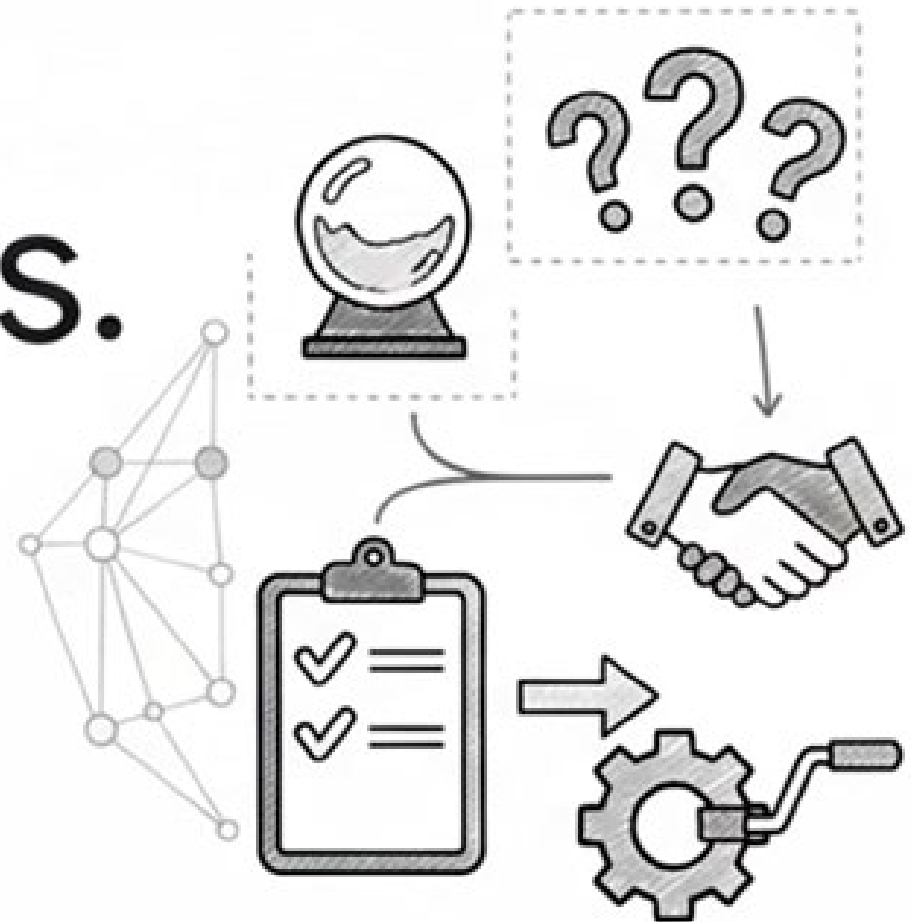




The **best time** to send is meaningless if it's the **wrong moment** to engage.

Prediction vs. Decision

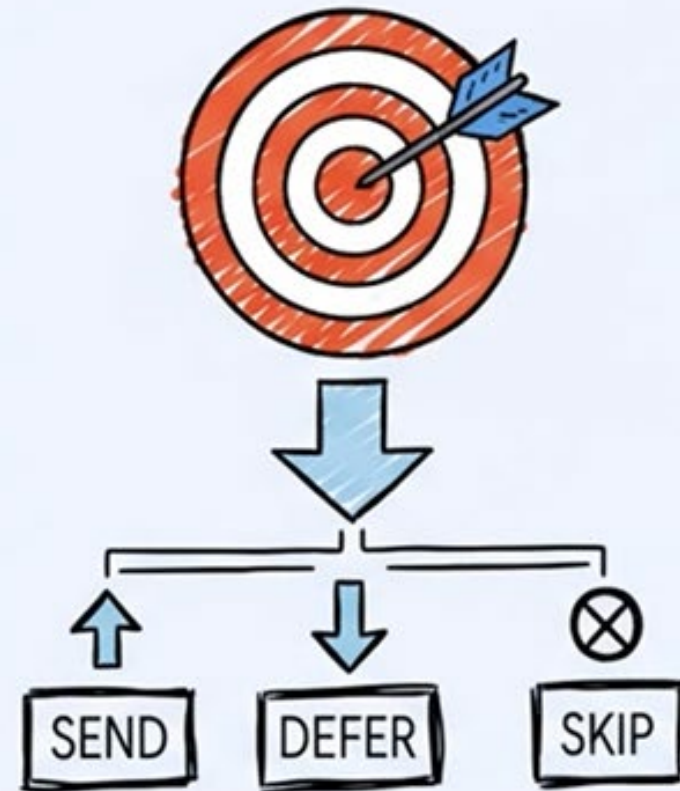
From Signal to Action



PREDICTION



DECISION



ML PREDICTION

OUTPUT:

- Probability score
- Confidence level
- "73% likely to engage"

CONSIDERS:

- Historical patterns
- Single model view
- User features

OWNERSHIP:

- Predicts likelihood
- No action taken

❑ Doesn't tell you WHAT TO DO

AI DECISION

OUTPUT:

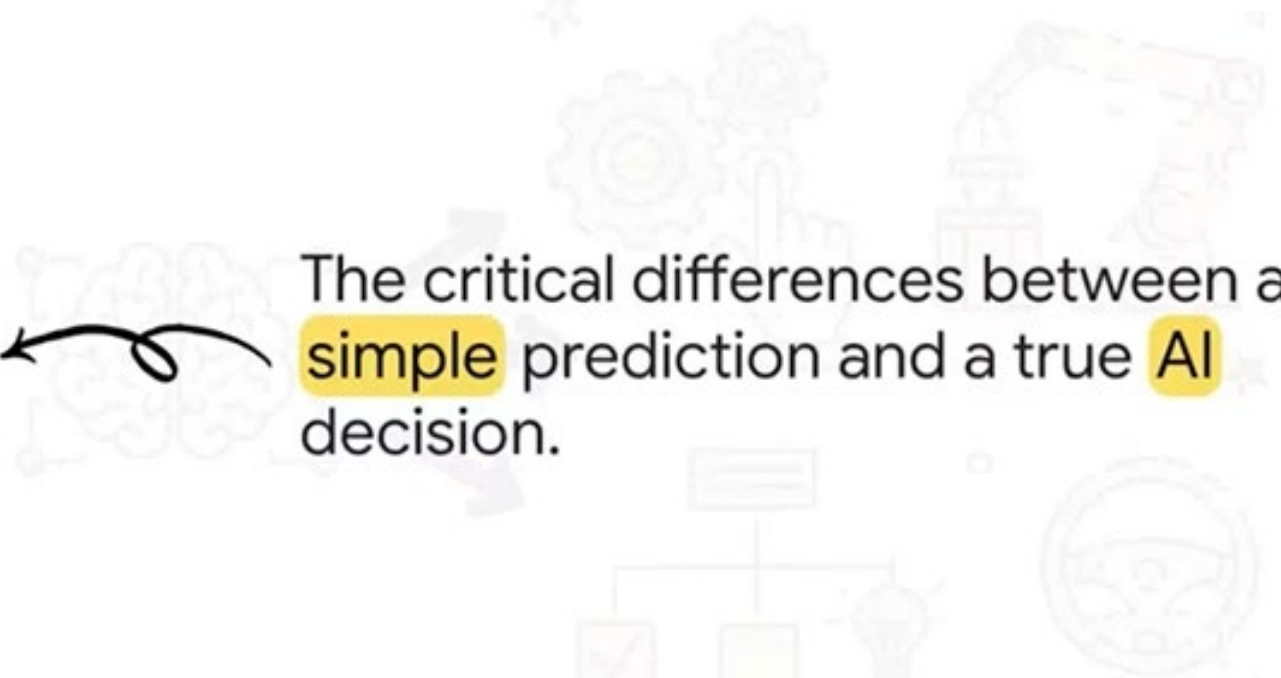
- Action (SEND/DEFER/SKIP)
- Reasoning
- "SEND because..."

CONSIDERS:

- Multiple ML signals
- Business constraints
- User state & fatigue
- Campaign priorities
- Real-time context

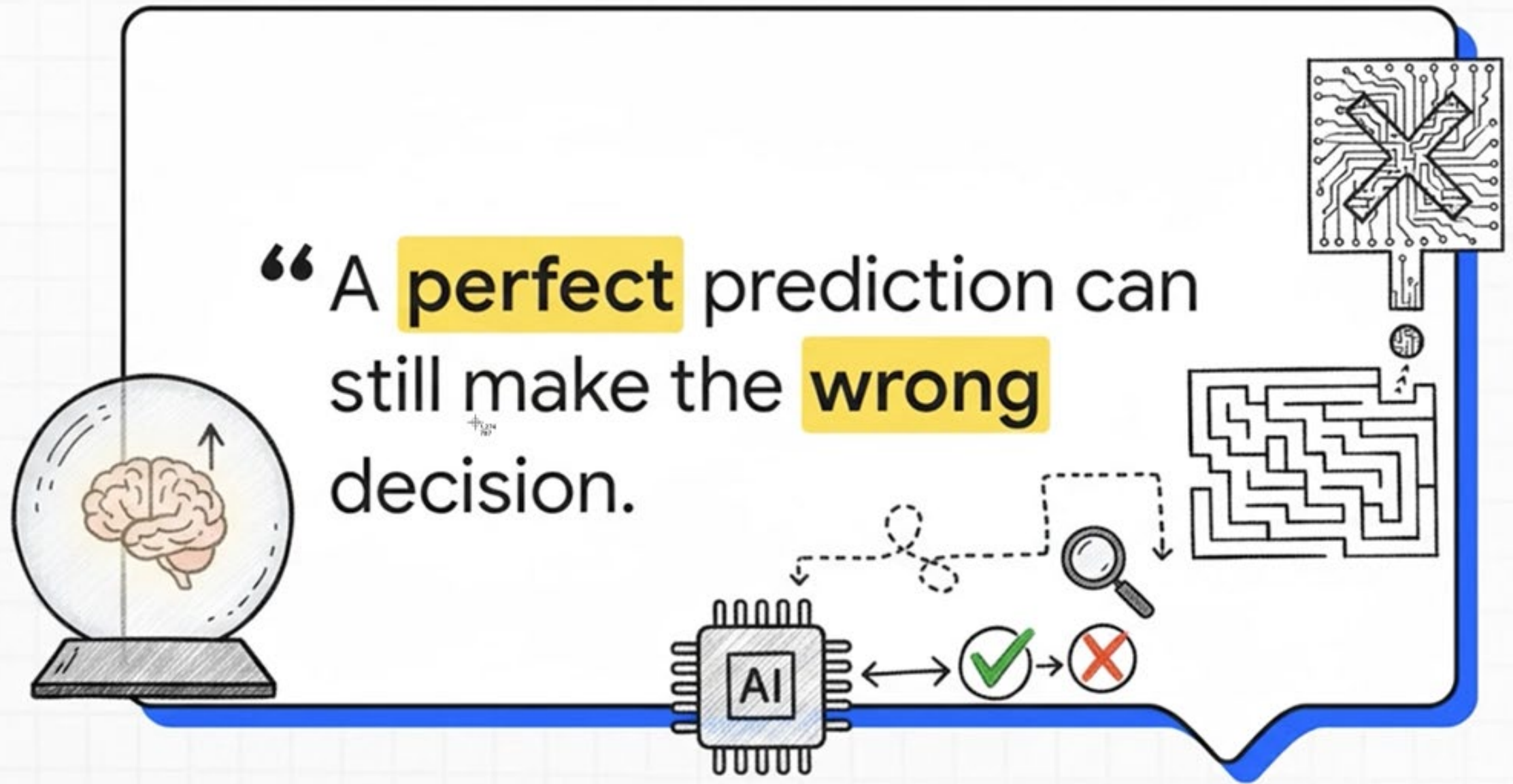
OWNERSHIP:

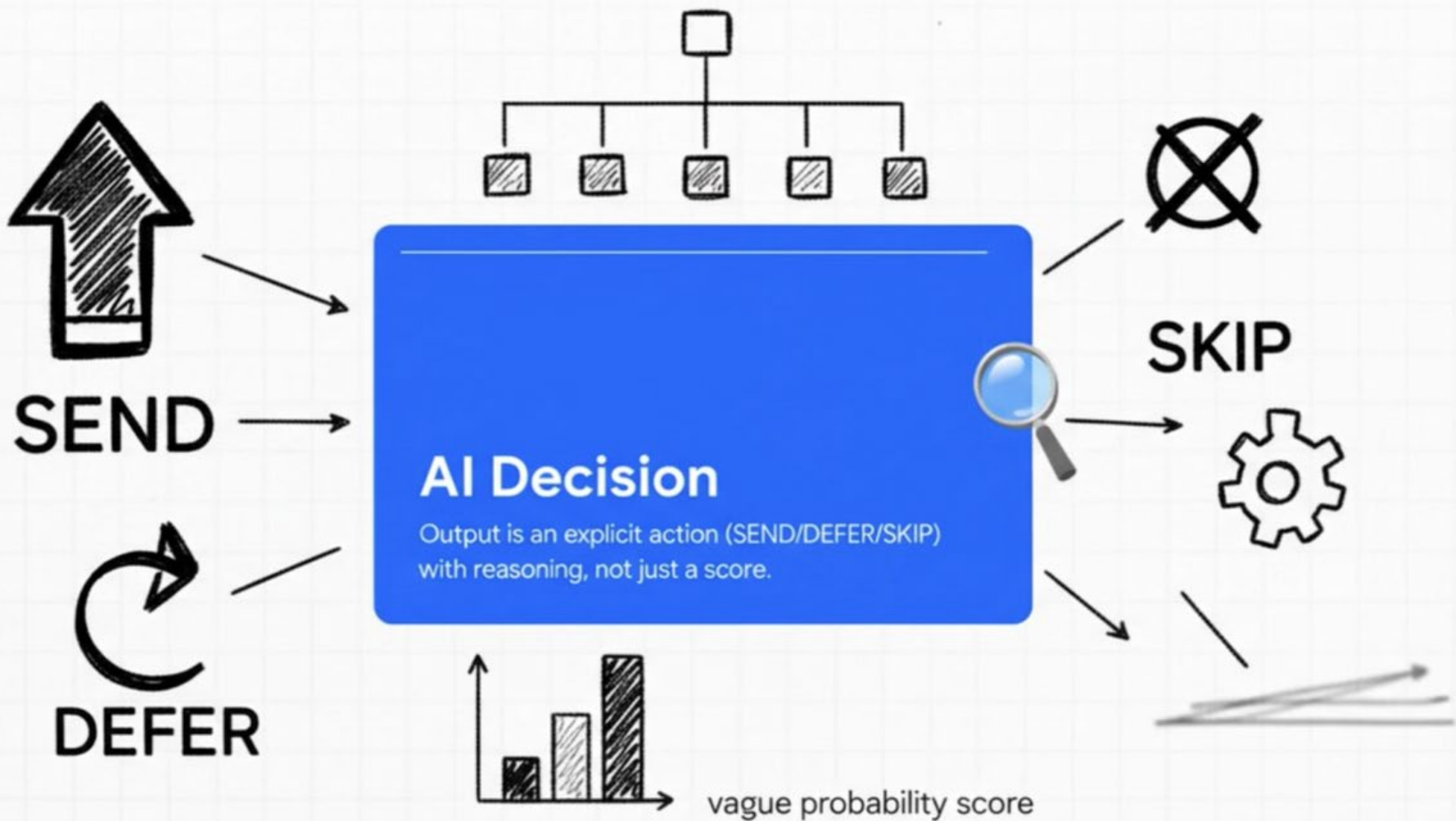
- Owns the outcome
- ✓ Tells you WHAT TO DO and WHY
- Executes decision



The critical differences between a simple prediction and a true AI decision.

“ A **perfect** prediction can still make the **wrong** decision.



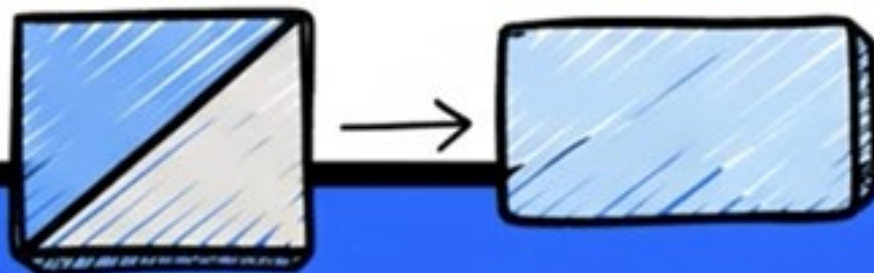


DEMO

How AI Decides

⚙️ The Decision Flow

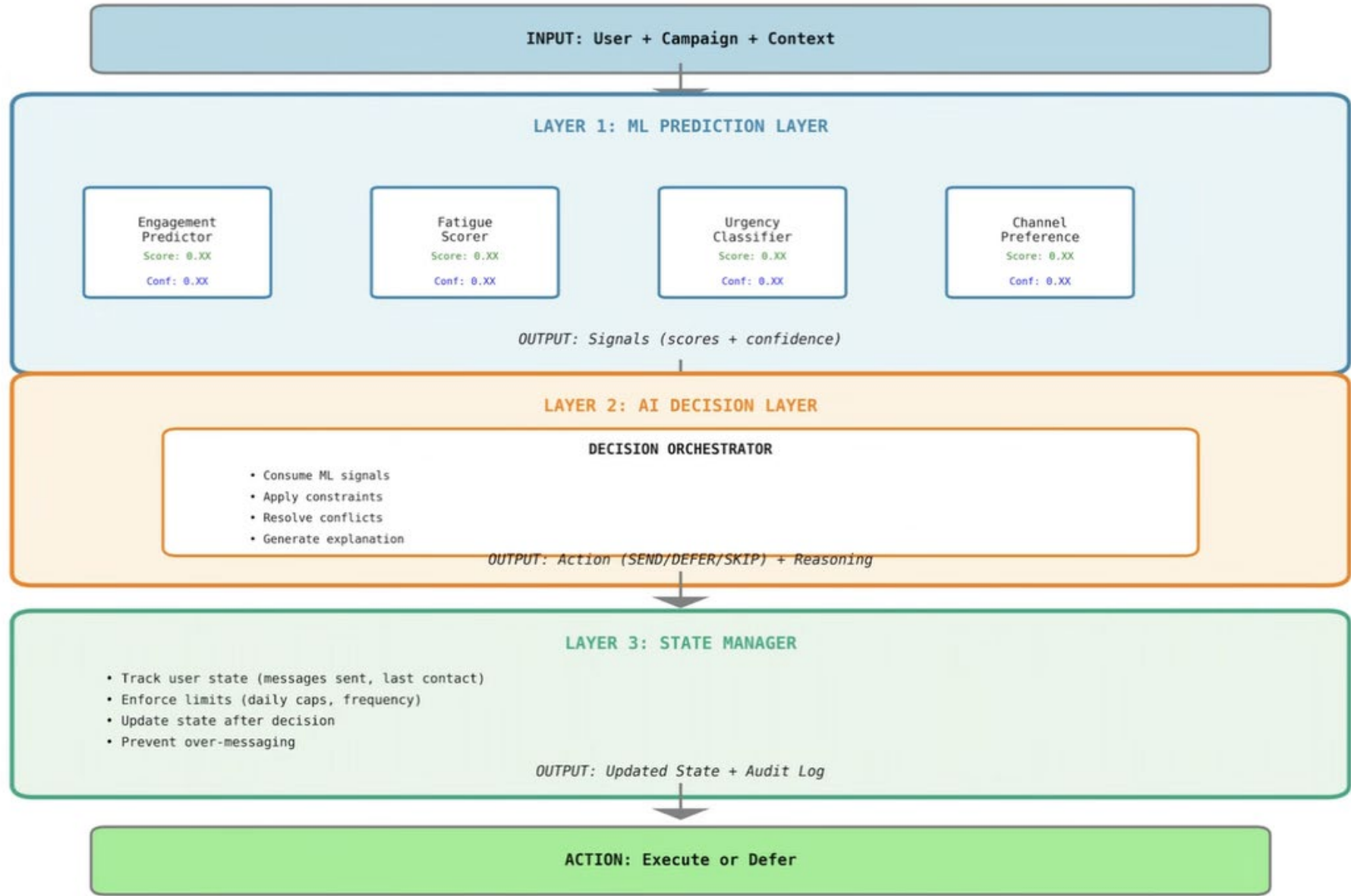
Three-layer Architecture



Decision

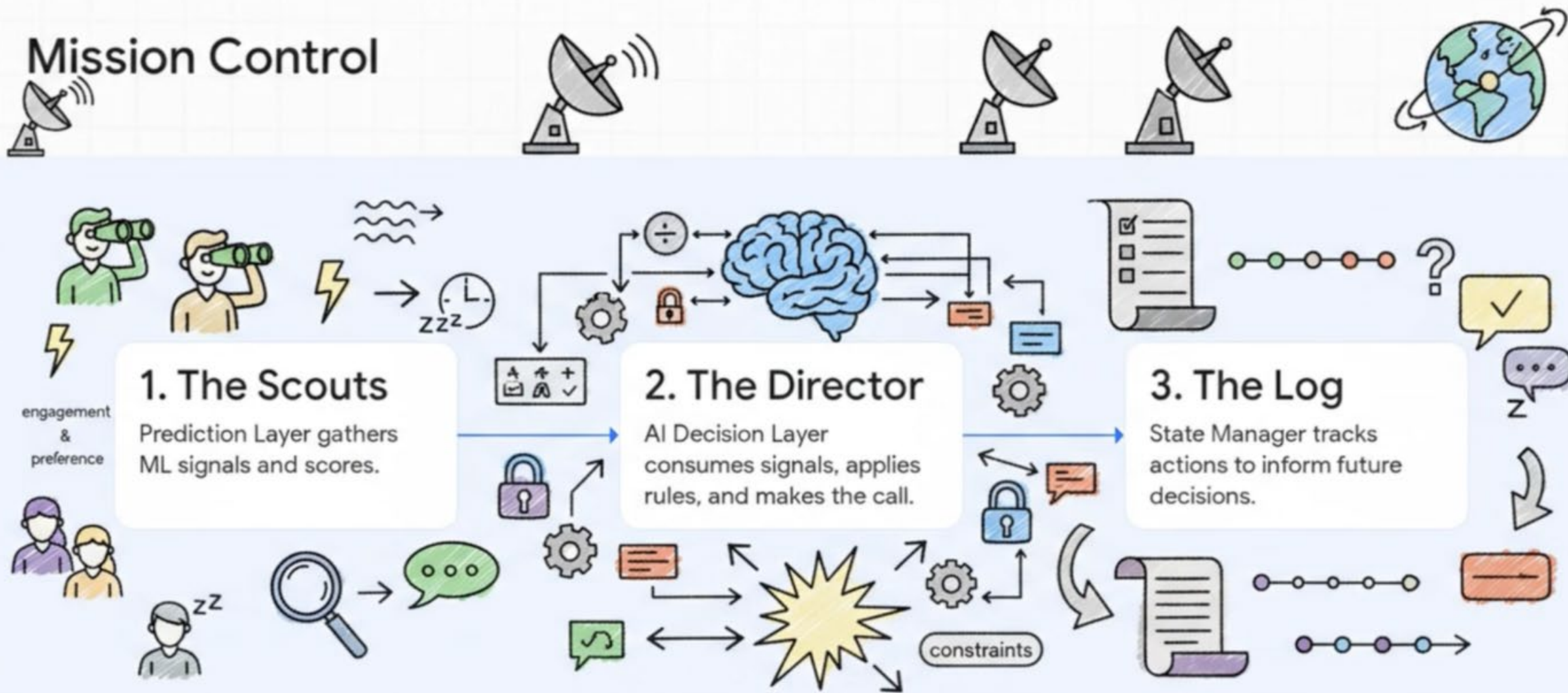


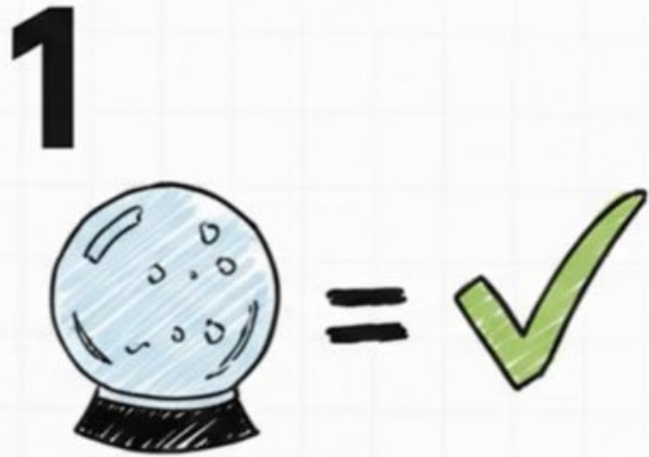
3-Layer Decisioning Architecture



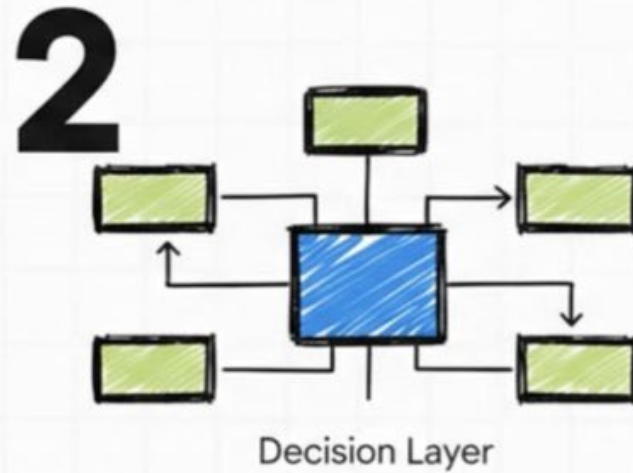
Separation of Concerns: ML predicts → AI decides → State enforces

Mission Control

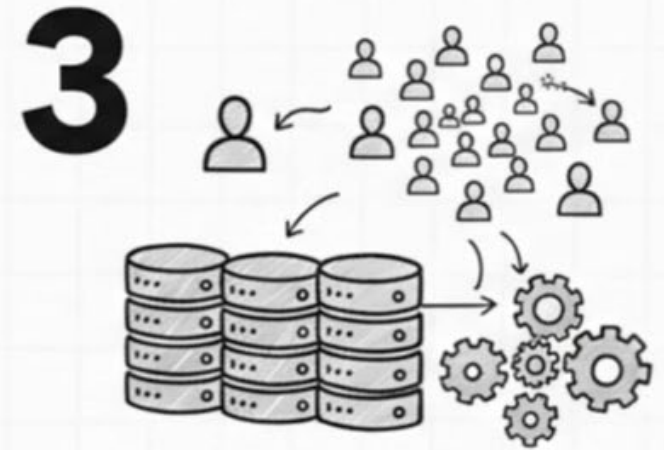




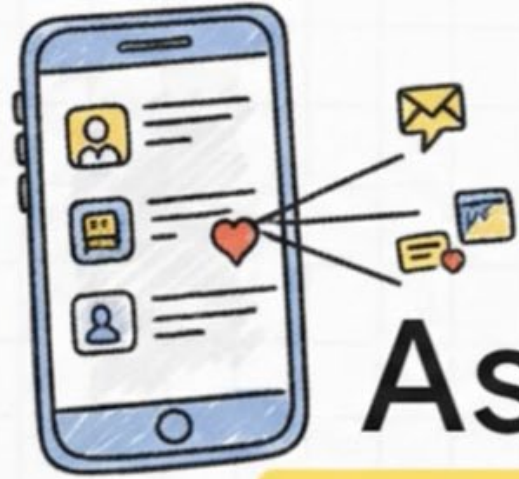
Prediction \neq Decision



Architecture Matters



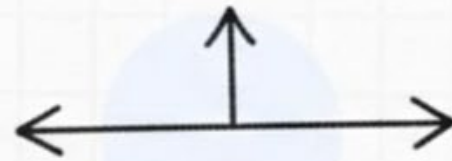
Scale Requires
Engineering



As brands use AI for
decisions, what does it
mean for **you**?



Personalized



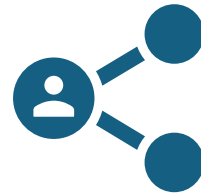
Something else?

Thank you



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Demo Code: github.com/chandrapatym/mlconf-demo

