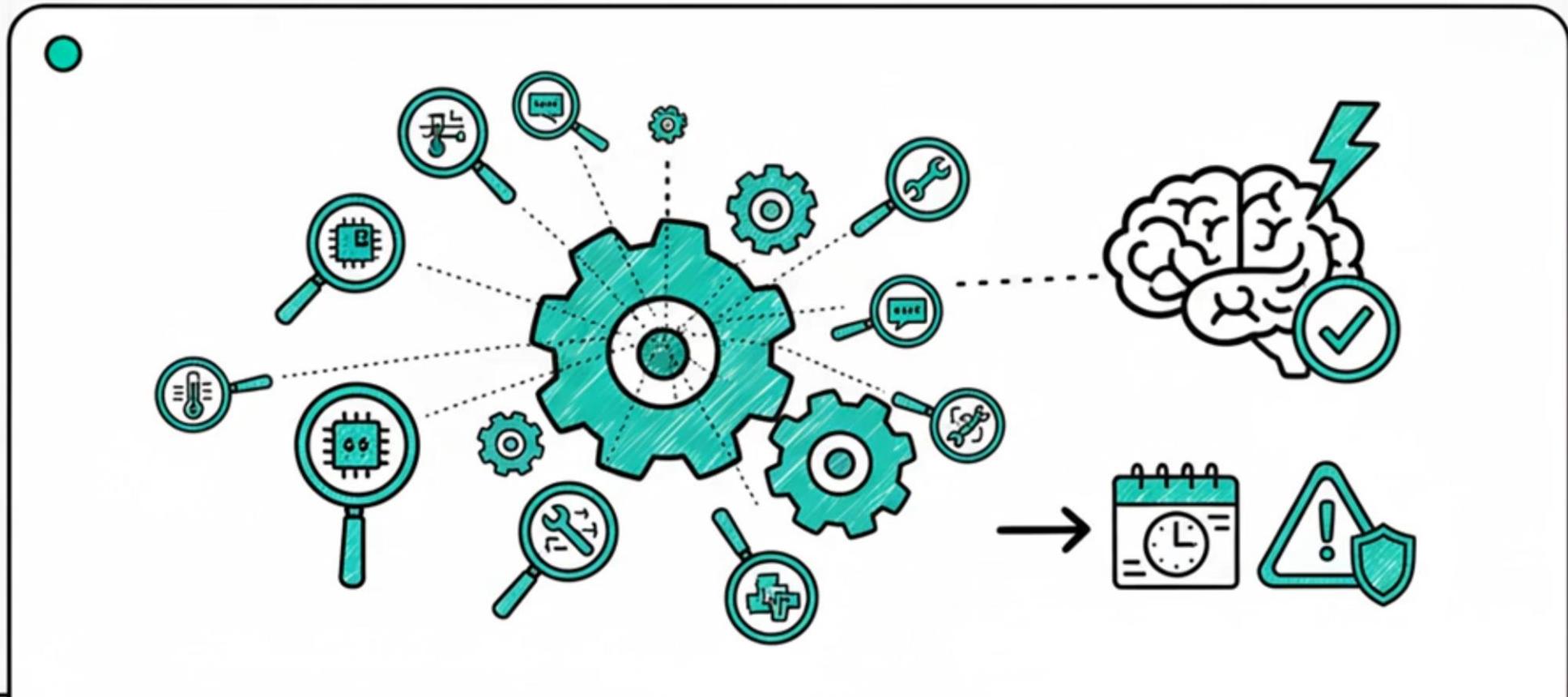


AI Ensemble for Predictive Maintenance



01

A High-Stakes
Prediction

02

The Power of
Teamwork

03

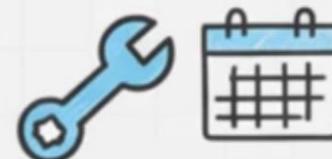
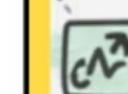
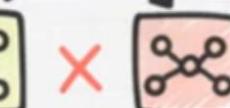
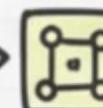
Two Main
Strategies

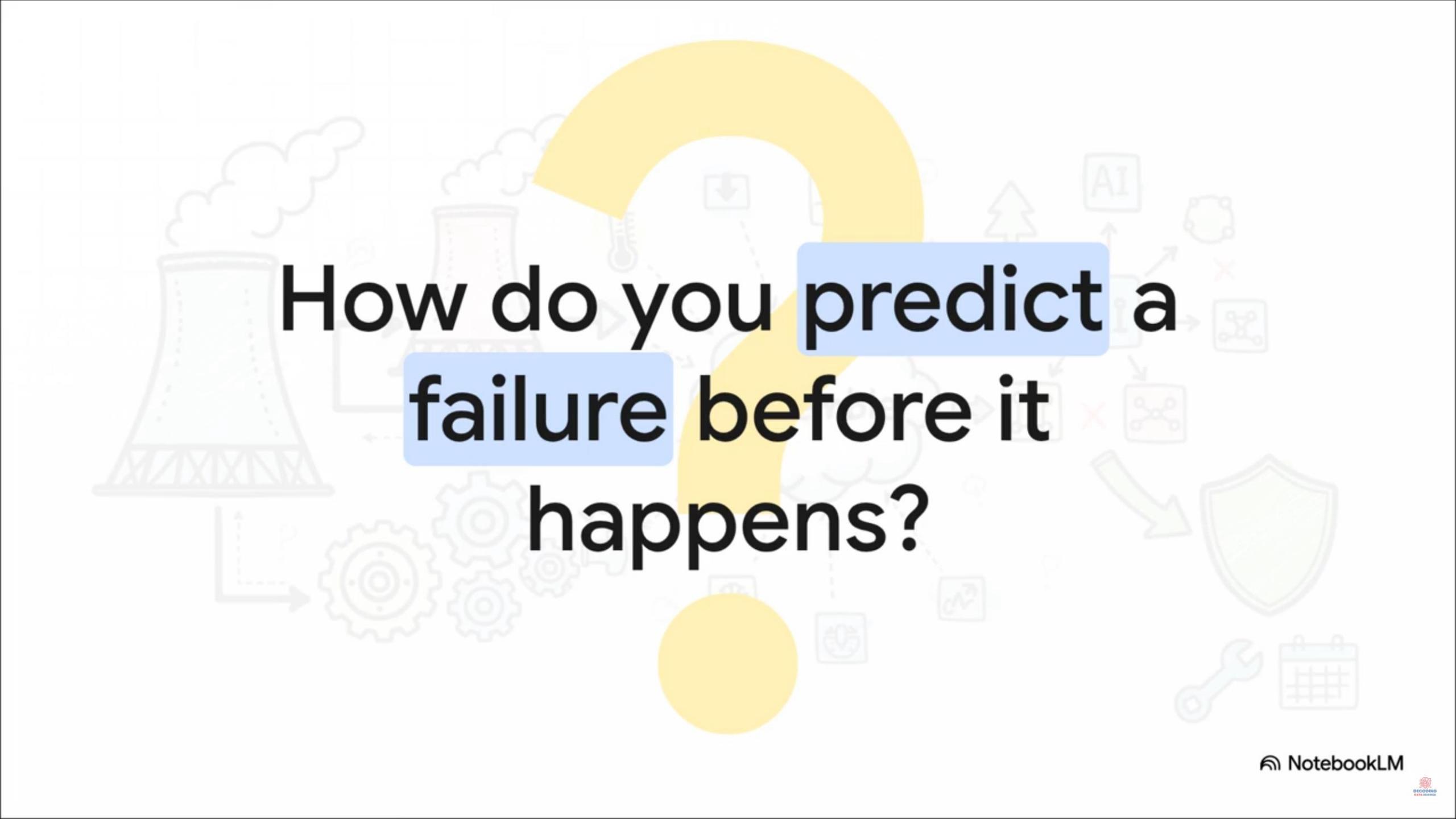
04

A Look at the
Code

05

Why Ensembles
Often Win

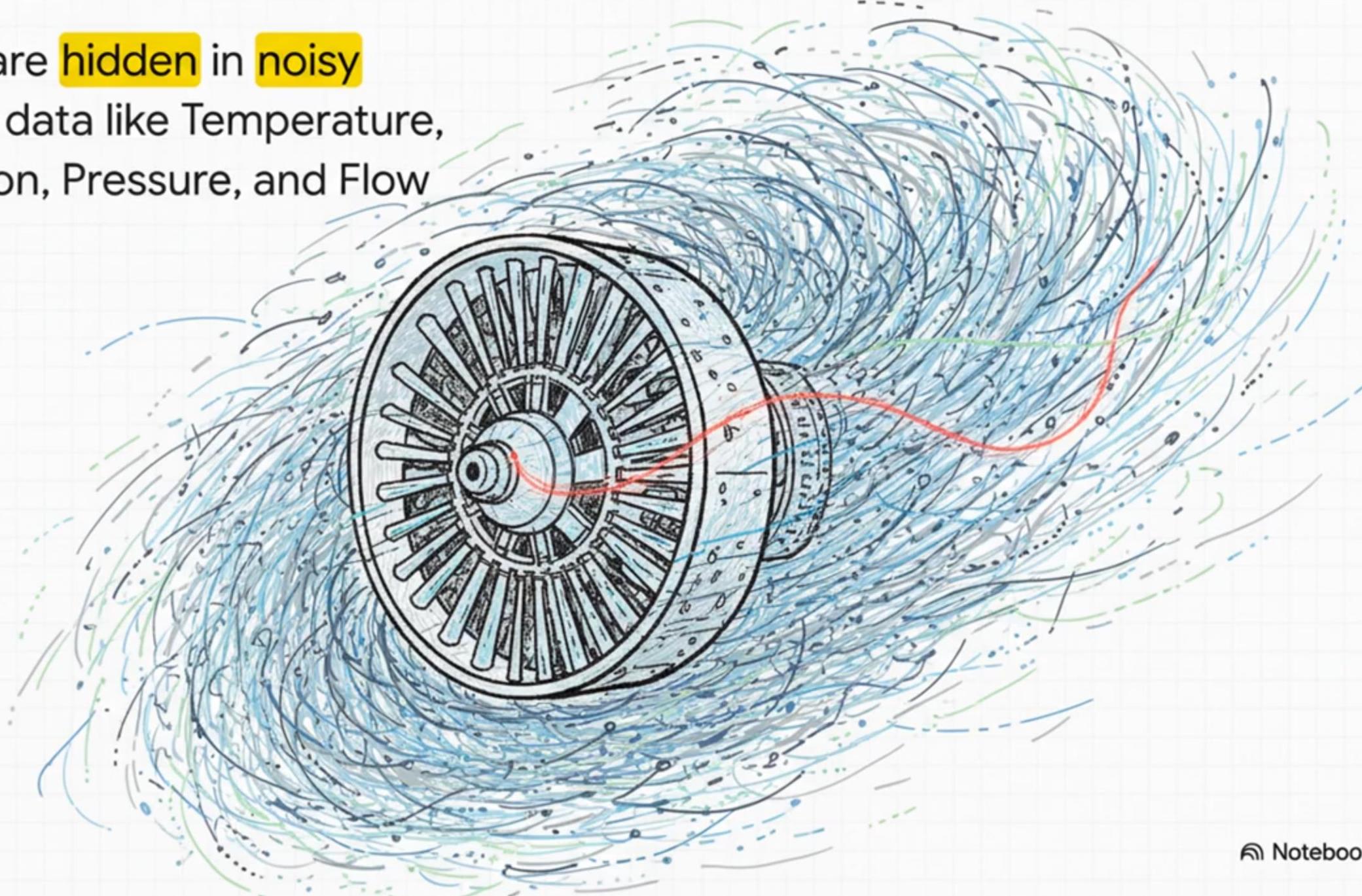




How do you predict a
failure before it
happens?



Clues are **hidden** in noisy
sensor data like Temperature,
Vibration, Pressure, and Flow
Rate.

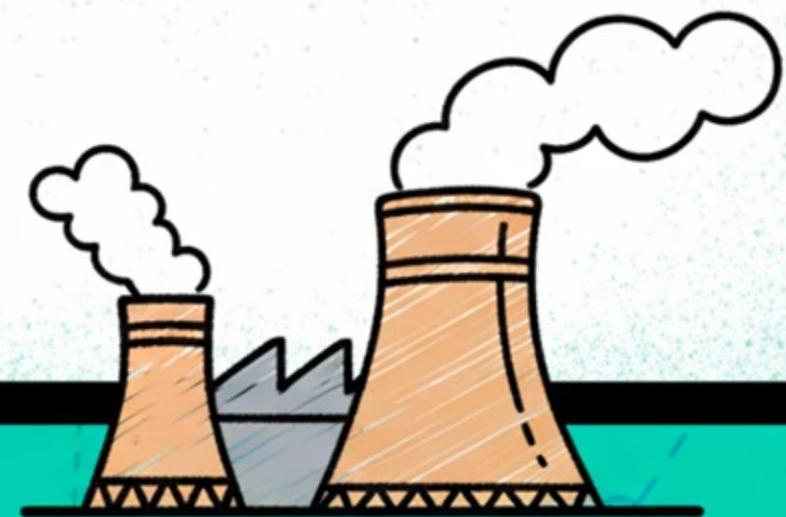


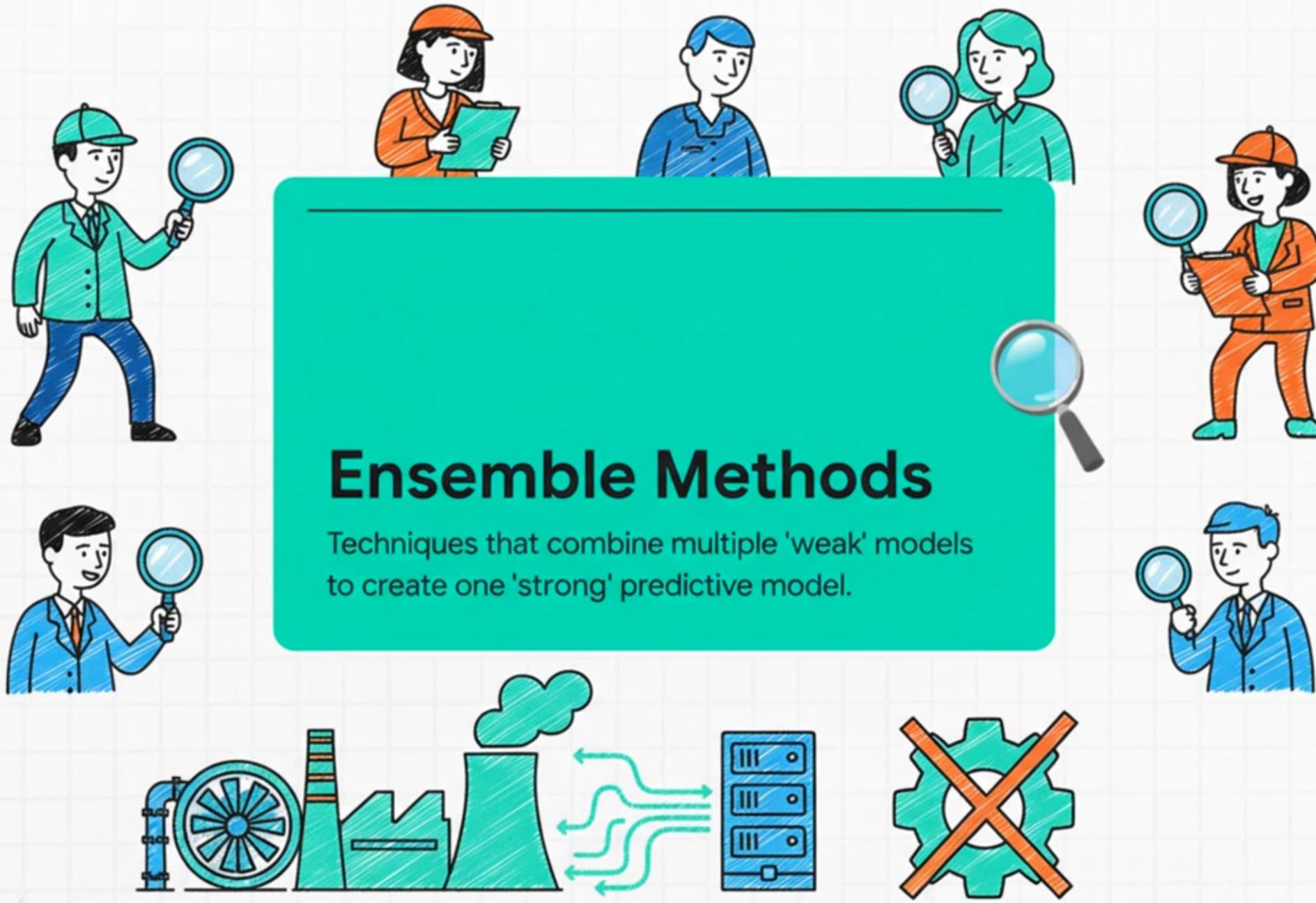
2



The Power of Teamwork

Ensemble Methods





The Power of the Team



BETTER
GENERALIZATION



MORE STABLE &
TRUSTWORTHY



HIGHER ACCURACY



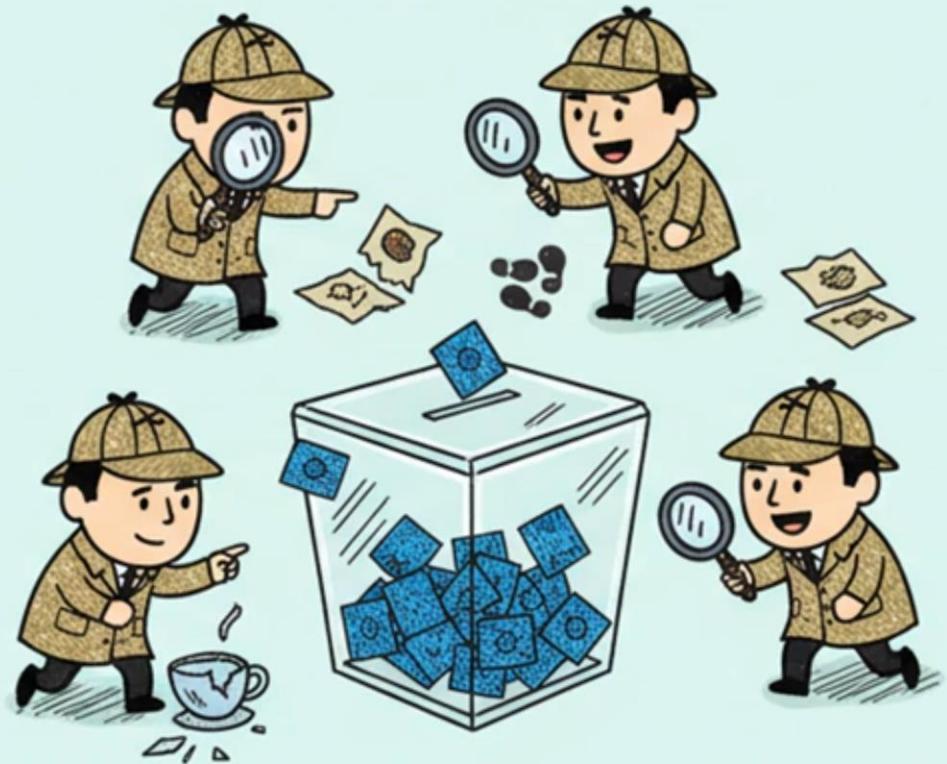
MORE ROBUST TO NOISE

Two Main Strategies

Bagging vs. Boosting



Bagging



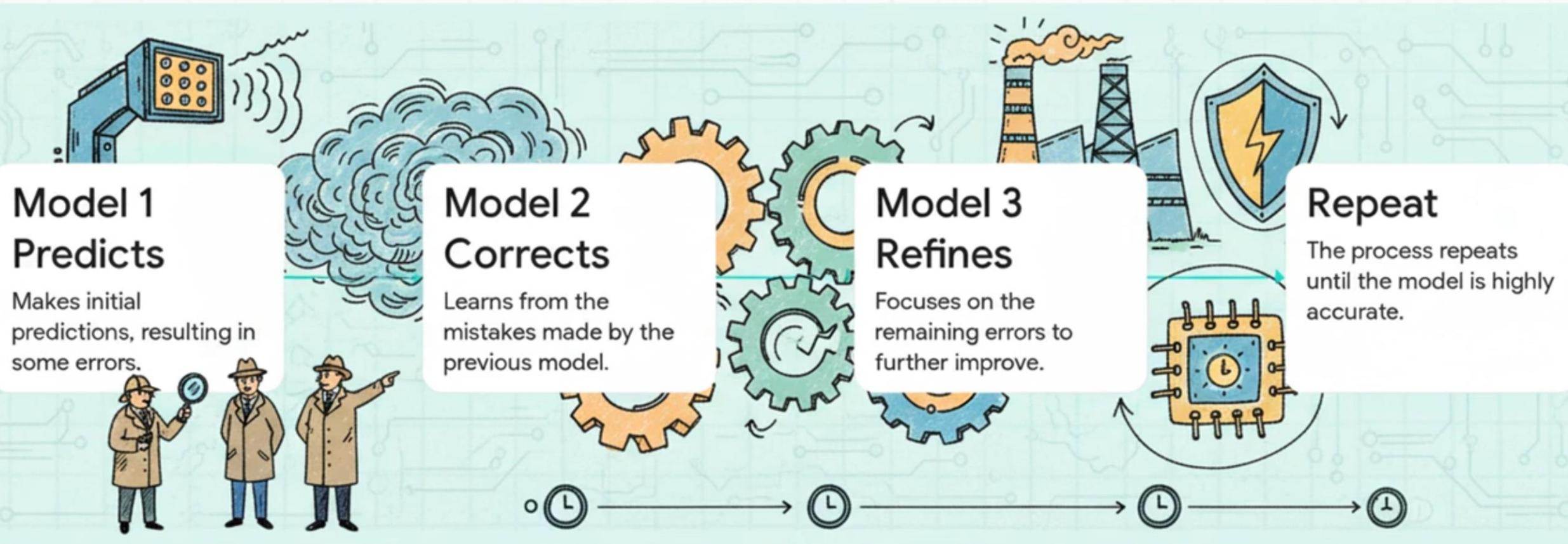
Boosting



Imagine a whole **forest** of
decision trees giving their
opinion. The final decision is a
vote, creating a stable,
balanced prediction.



Gradient Boosting



4

A Look at the Code

A Simple Example





How the Code Works



1. Generate Data

Create synthetic sensor data (temp, vibration, pressure).

2. Define Failure

Create a rule for what constitutes a 'failure' pattern.

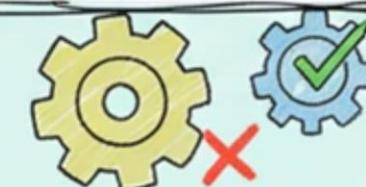
3. Train Model

Build a Random Forest model to learn the failure pattern.



4. Test Performance

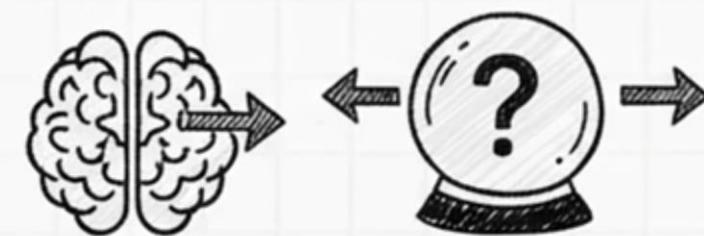
See how well the model predicts failures on new, unseen data.



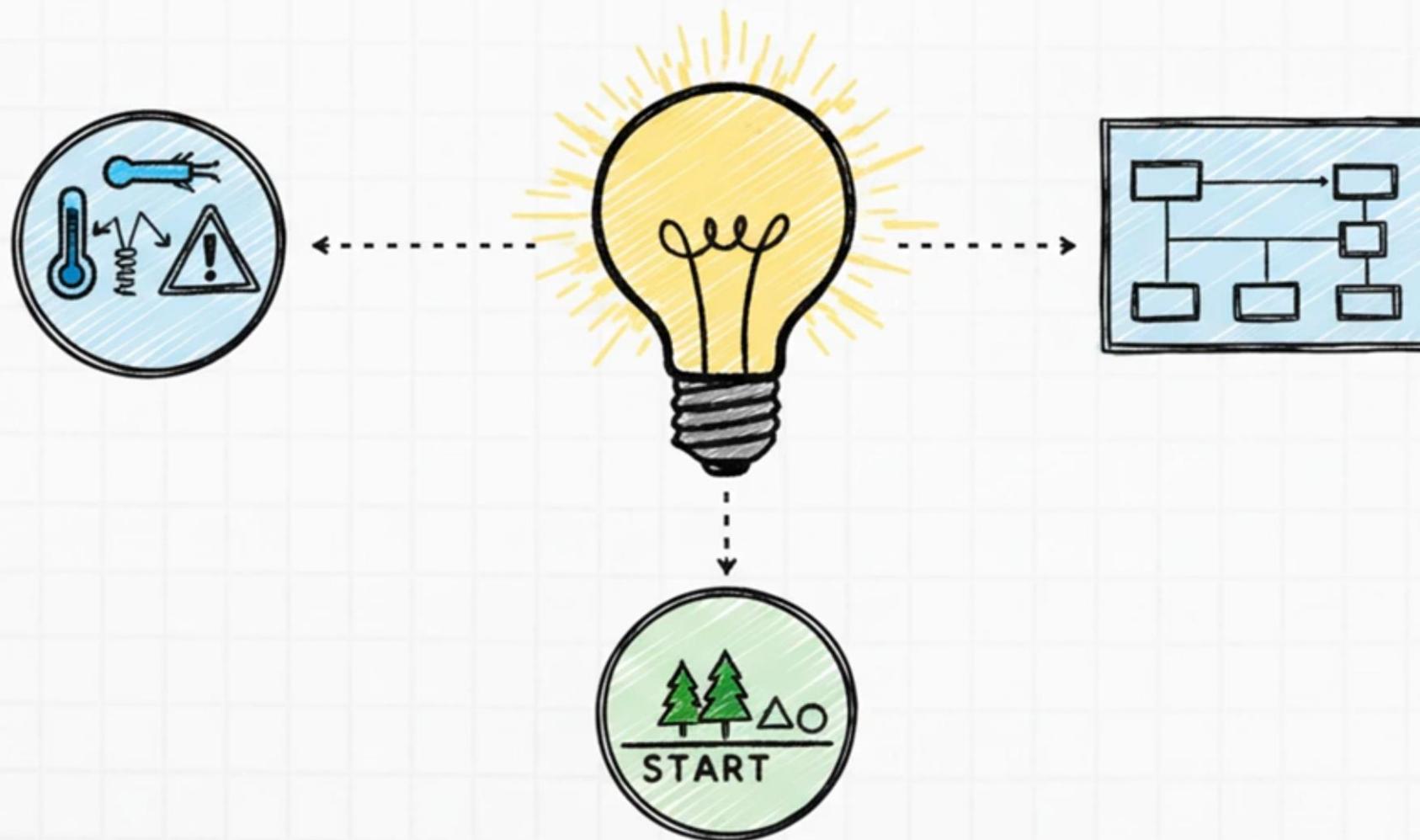
Key Code Lines



```
• from sklearn.ensemble import RandomForestClassifier  
• model = RandomForestClassifier(n_estimators=50)  
• model.fit(X_train, y_train)  
• y_pred = model.predict(X_test)
```



What This Teaches Us

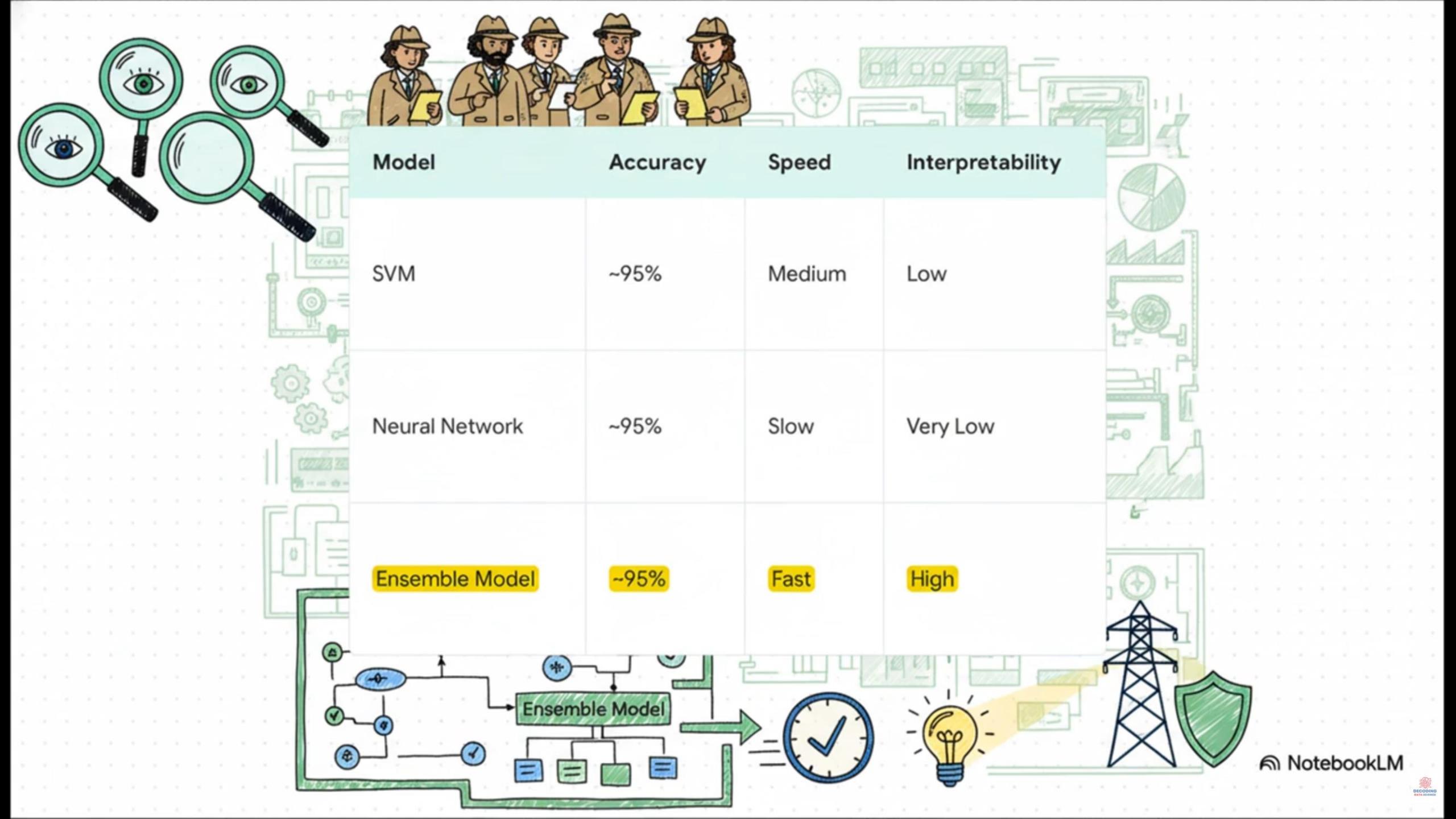




Why Ensembles Often Win

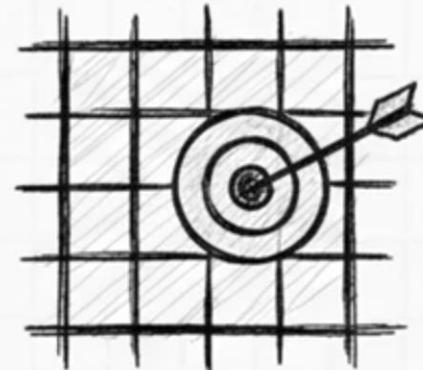
The Final Verdict



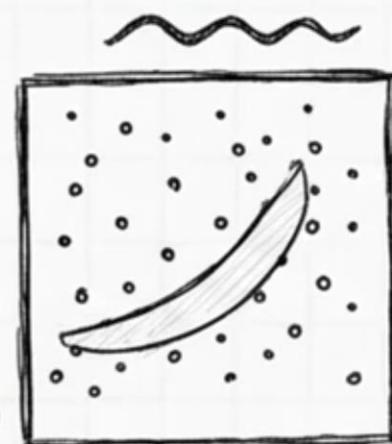


Key Technical Benefits

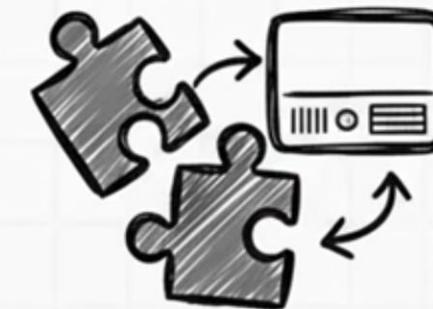
- High accuracy on tabular sensor data
- Excellent at handling non-linear relationships
- Reduces variance and prevents overfitting
- Works well even with limited data



Overfitting



Good Fit



The Final Verdict

Combining simple models to
create one strong predictor





So, when shouldn't you
use them?