

What's next for ML & you

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Deploying an ML service

What is Production?



Serving live predictions

Deployment

Measuring quality of deployed models



Evaluation



Choosing between deployed models

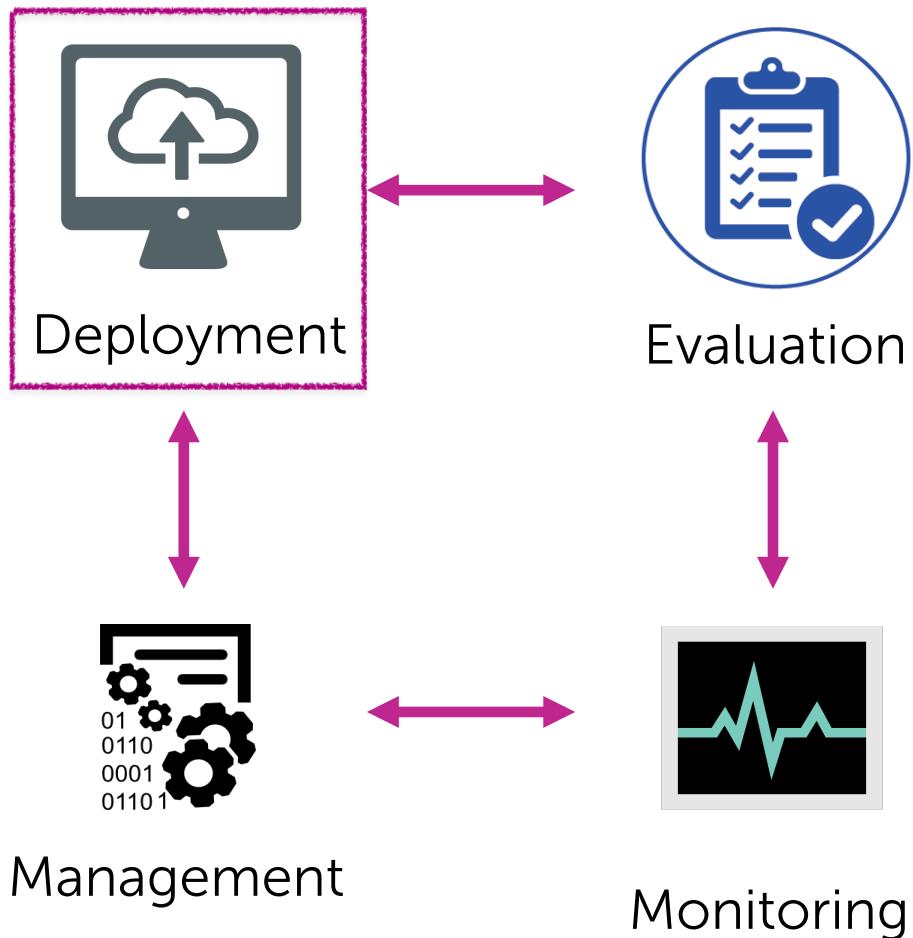
Management

Tracking model quality & operations



Monitoring

Lifecycle of ML in Production

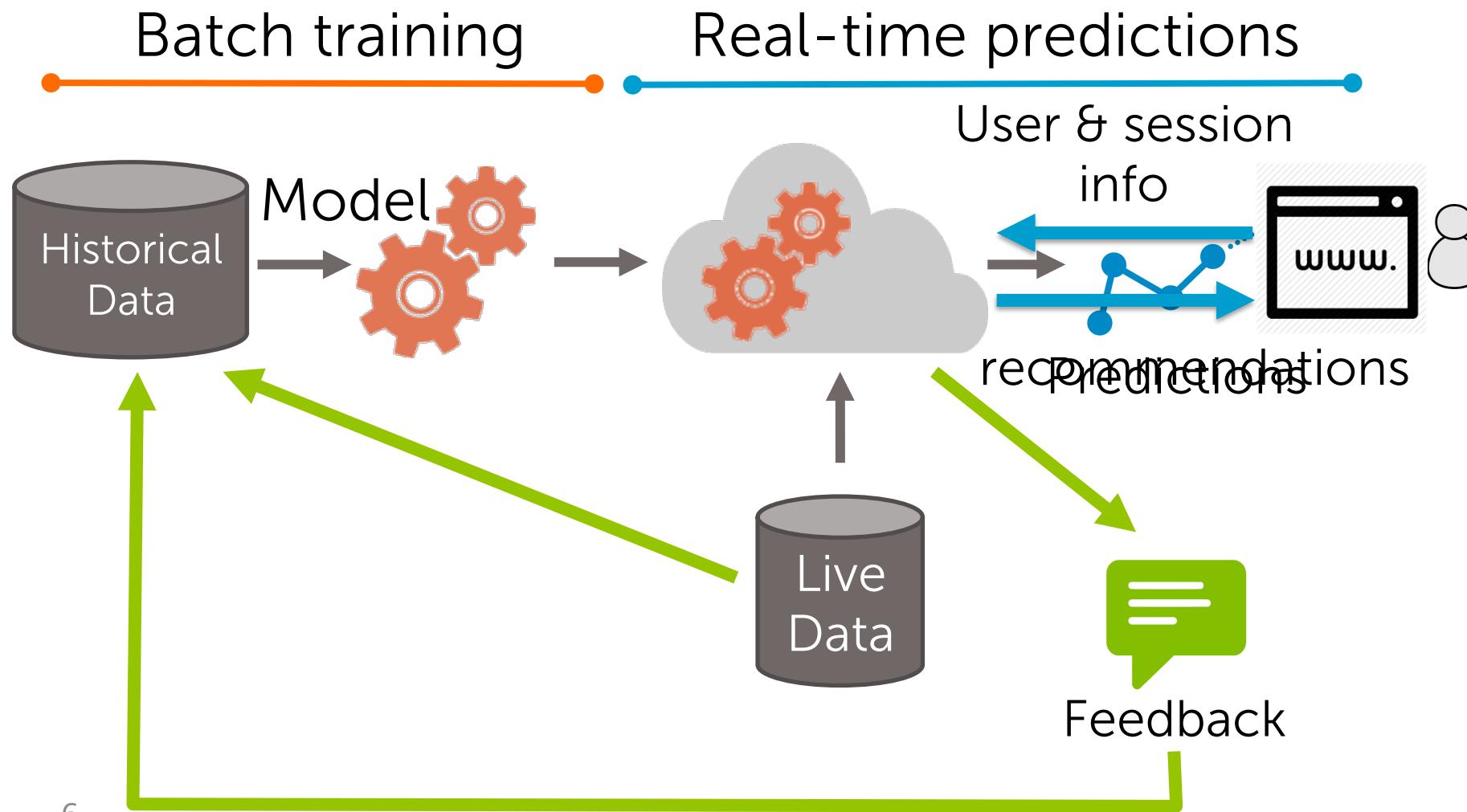


The Setup...

Suppose we are building a website with
product recommendations,
trained using user reviews.

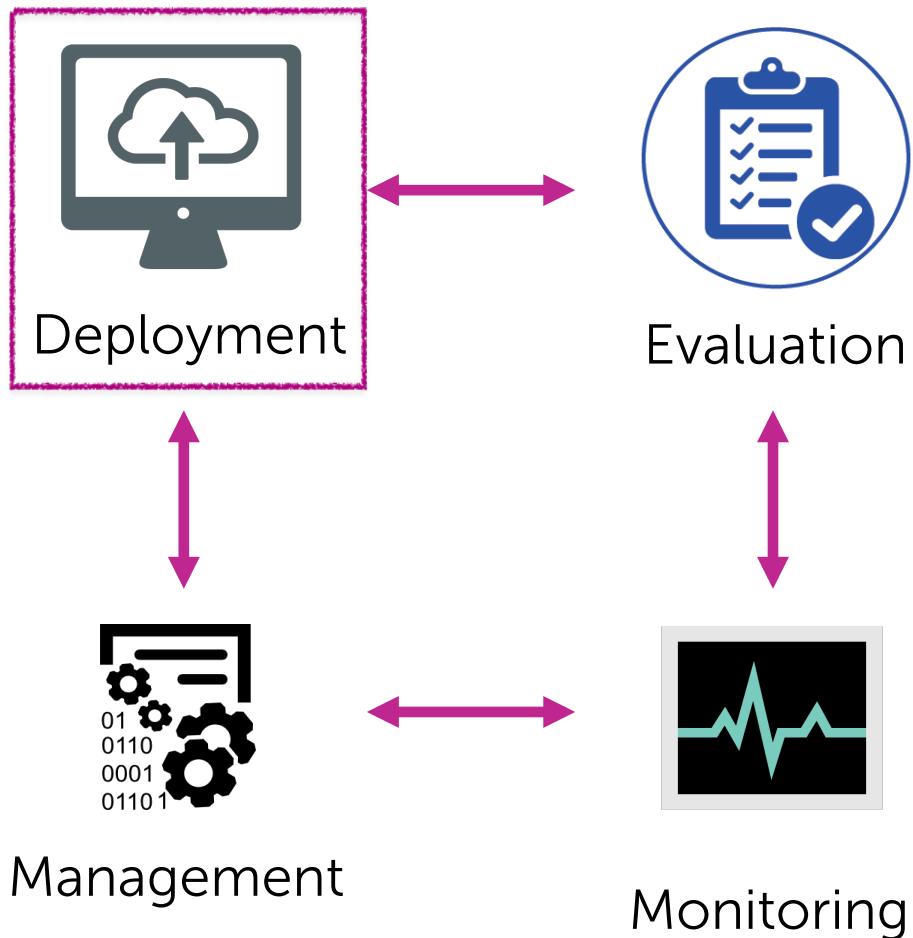
- 34.6M reviews
- 2.4M products
- 6.6M users

Deployment System



What happens after (initial) deployment

Lifecycle of ML in Production



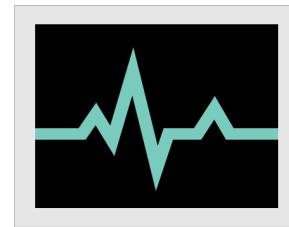
After deployment



Evaluation



Management

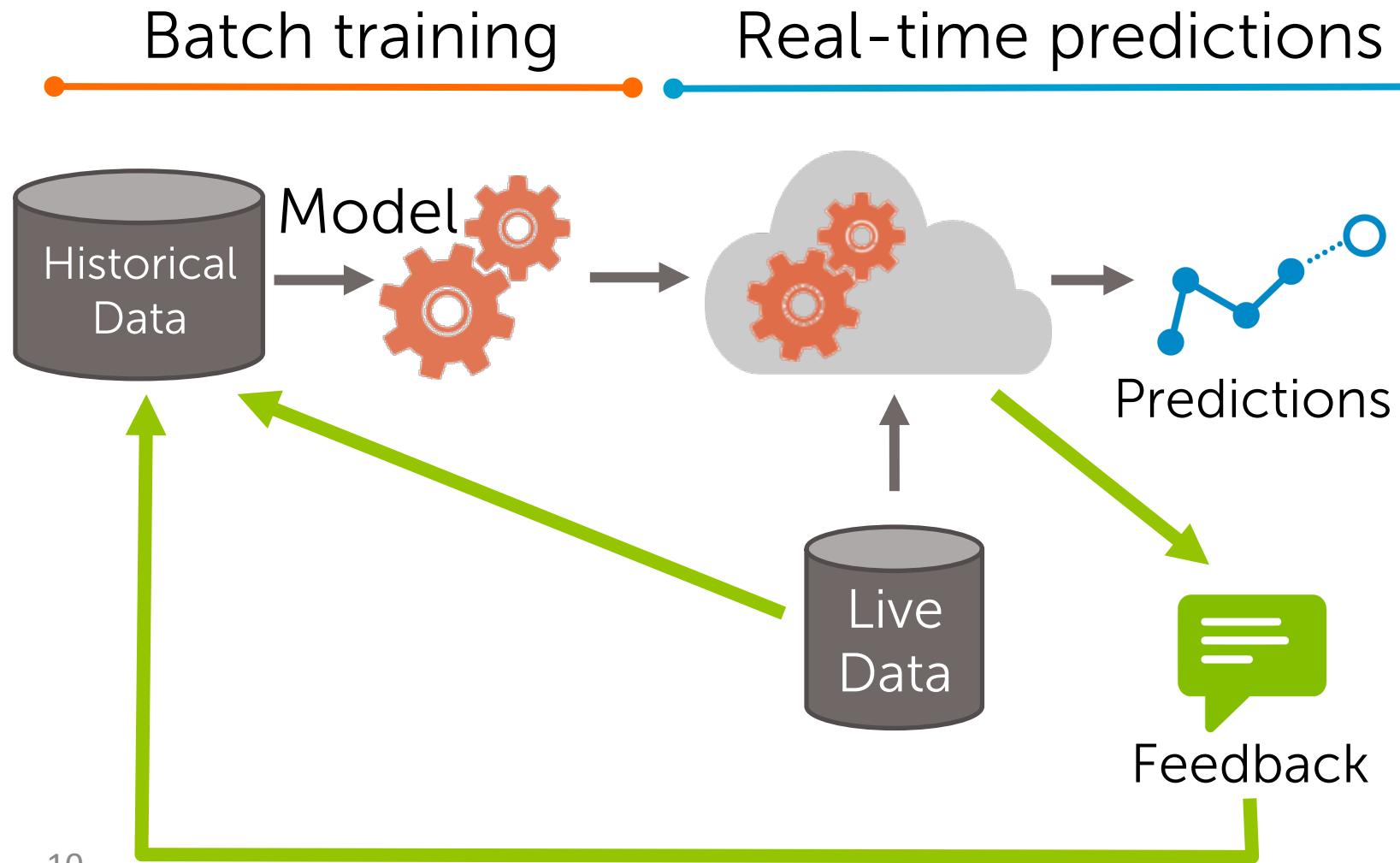


Monitoring

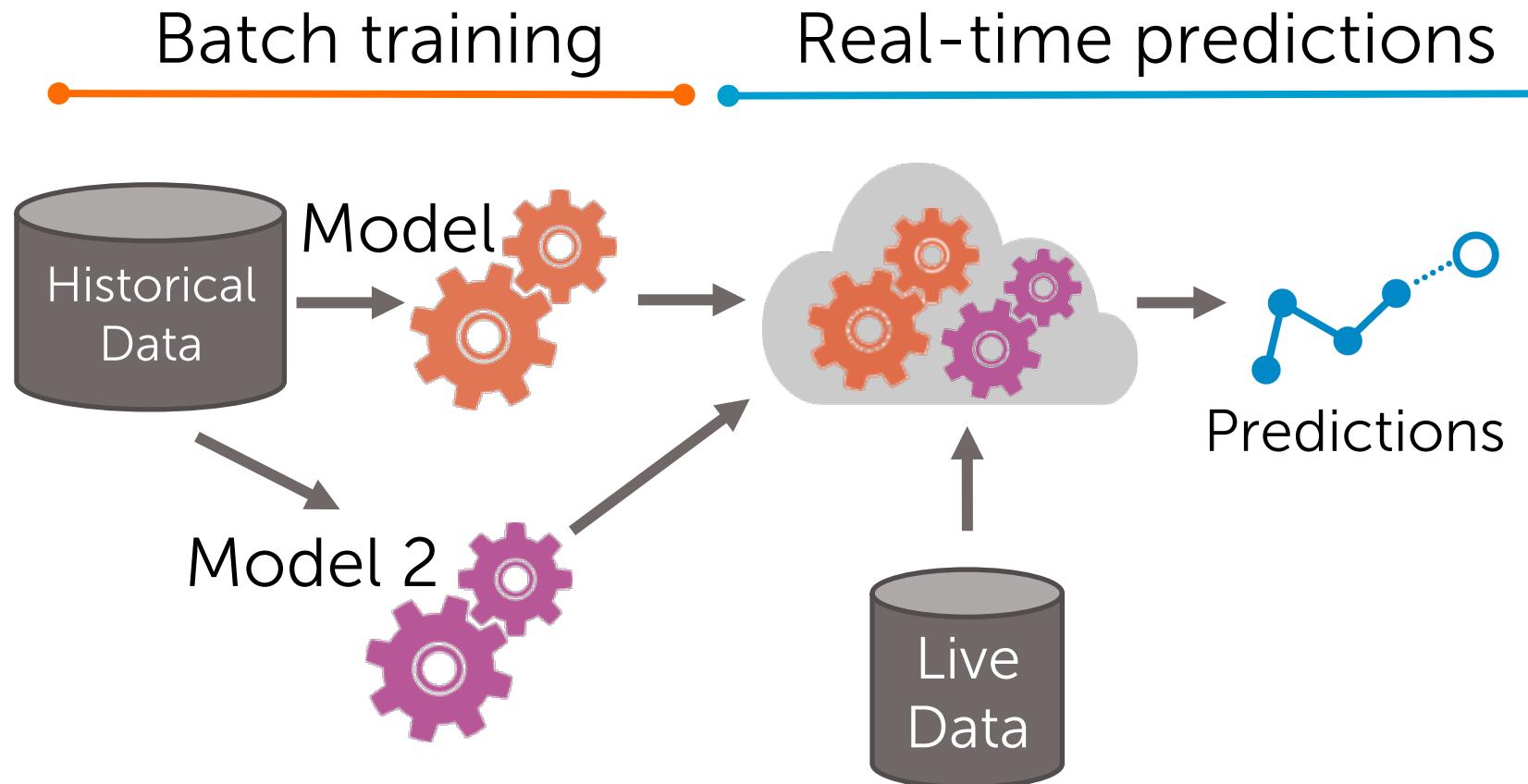
Evaluate and track metrics over time

React to feedback from deployed models

Feedback loop for ML in production



Learning new, alternative models



Key questions

- When to update a model?
- How to choose between existing models?
- Answer: continuous evaluation and testing

What is evaluation?



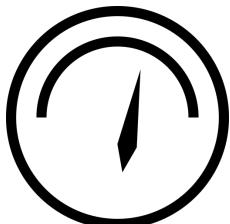
Evaluation

=



Predictions

+

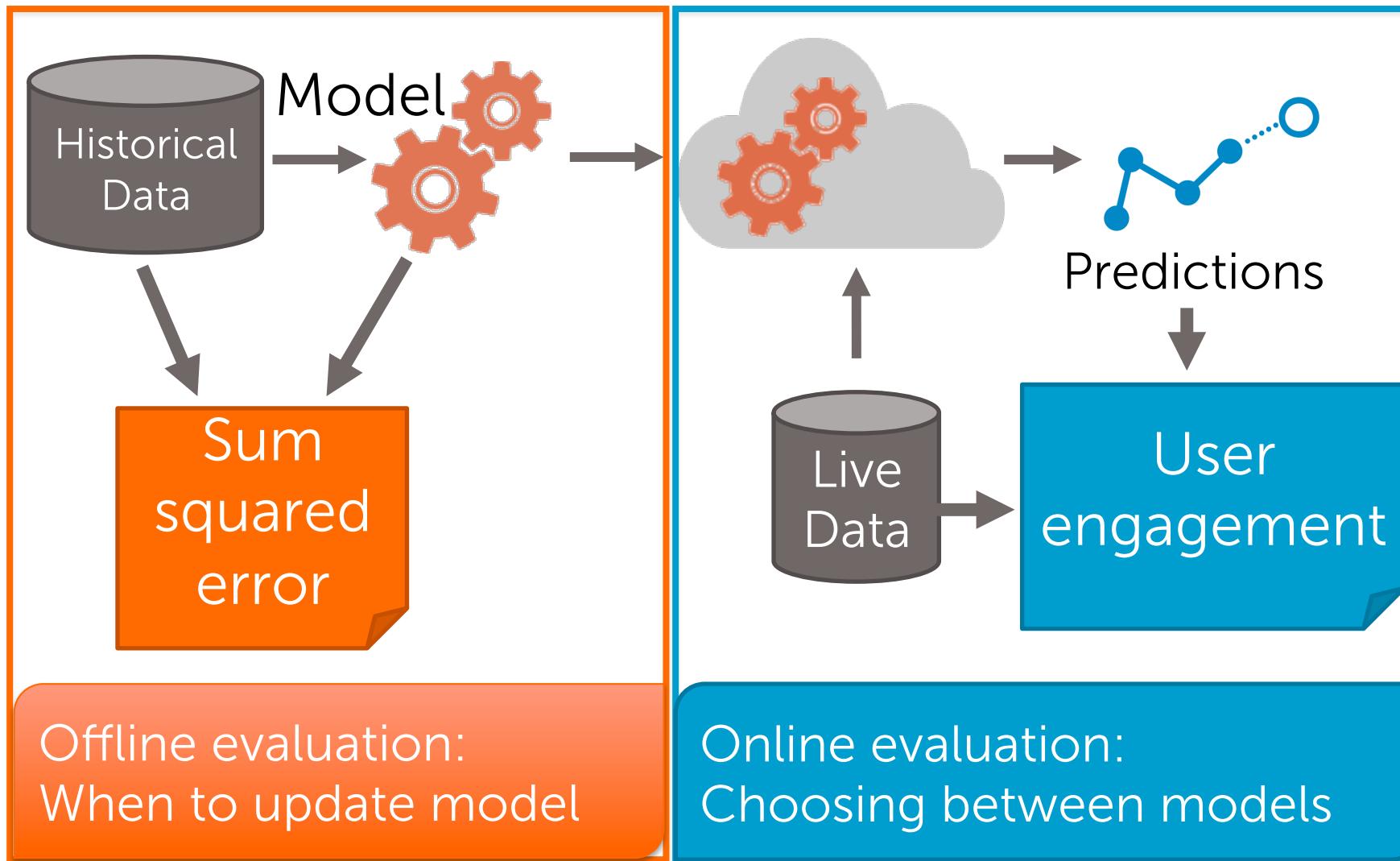


Metric

What data?

Which metric?

Evaluating a recommender



Updating ML models

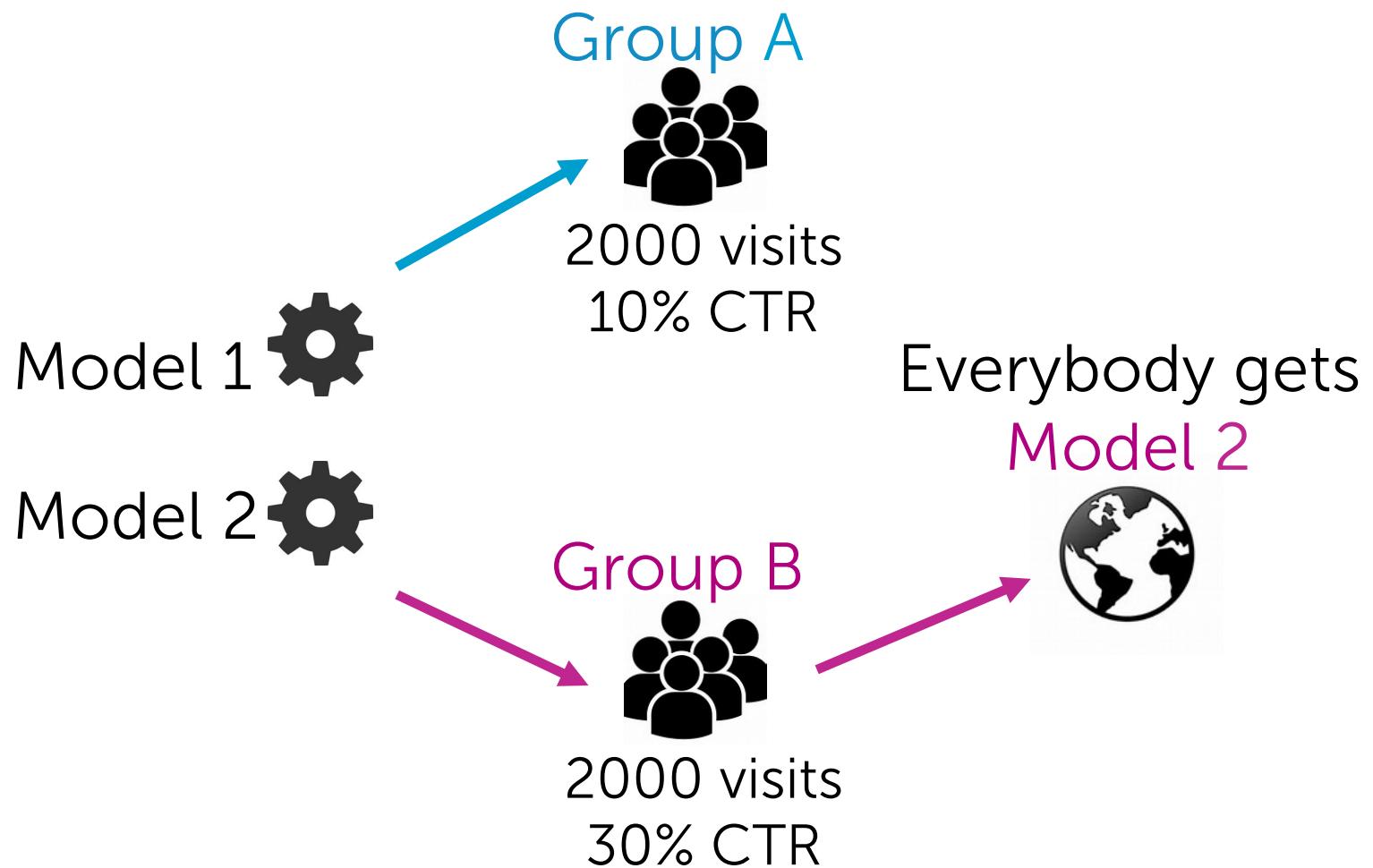
Why update?

- Trends and user tastes change over time
- Model performance drops

When to update?

- Track statistics of data over time
- Monitor both offline & online metrics
- Update when offline metric diverges from online metrics or not achieving desired targets

A/B Testing: Choosing between ML models

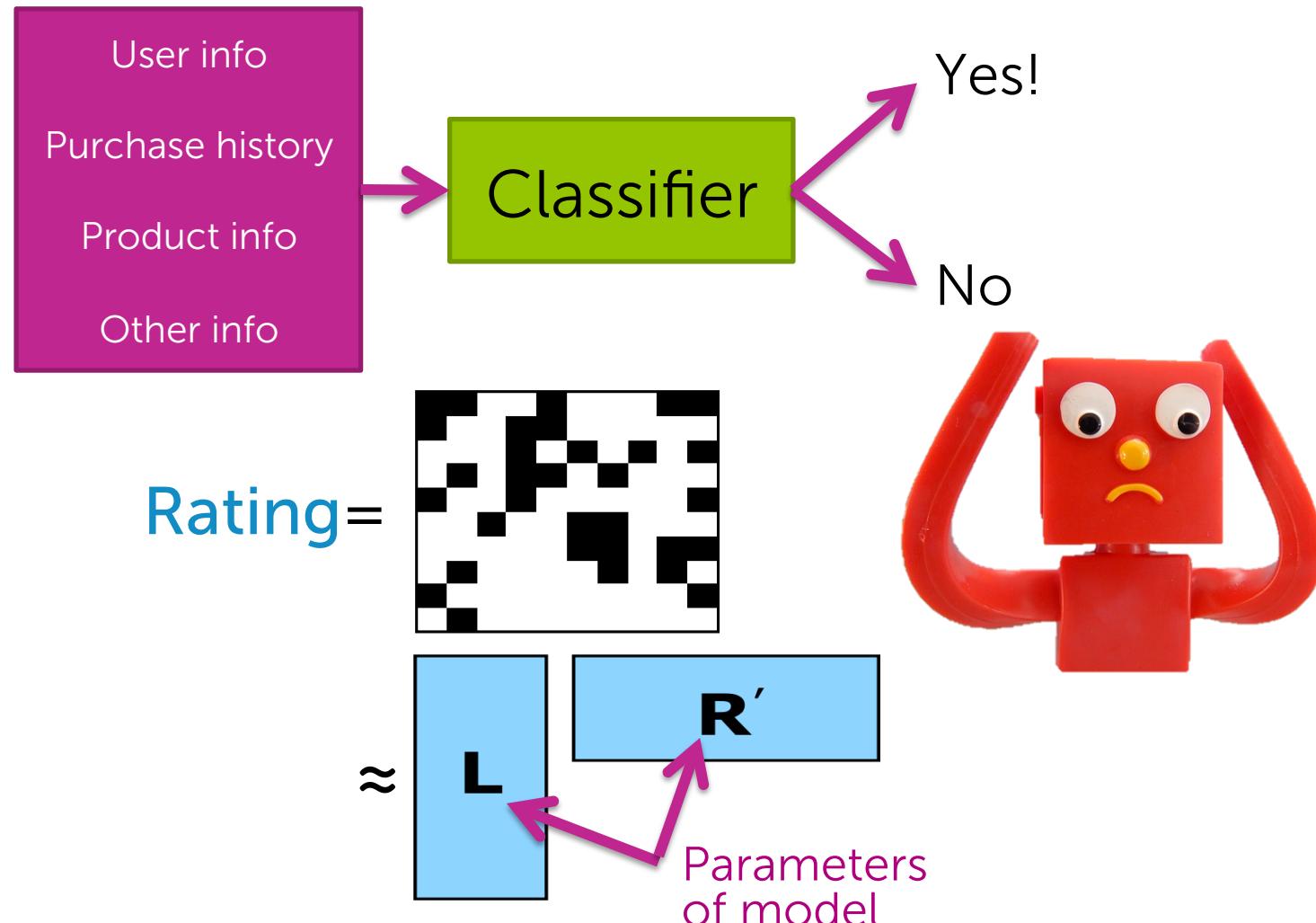


Other production considerations

- A/B testing caveats
 - Also multi-armed bandits
- Versioning
- Provenance
- Dashboards
- Reports
- ...

Machine learning challenges

Open challenges: Model selection



Open challenges: Feature engineering/representation



- Bag of word raw counts?
- Normalize?
- tf-idf? (which version???)
- Bigrams
- Trigrams
- ...

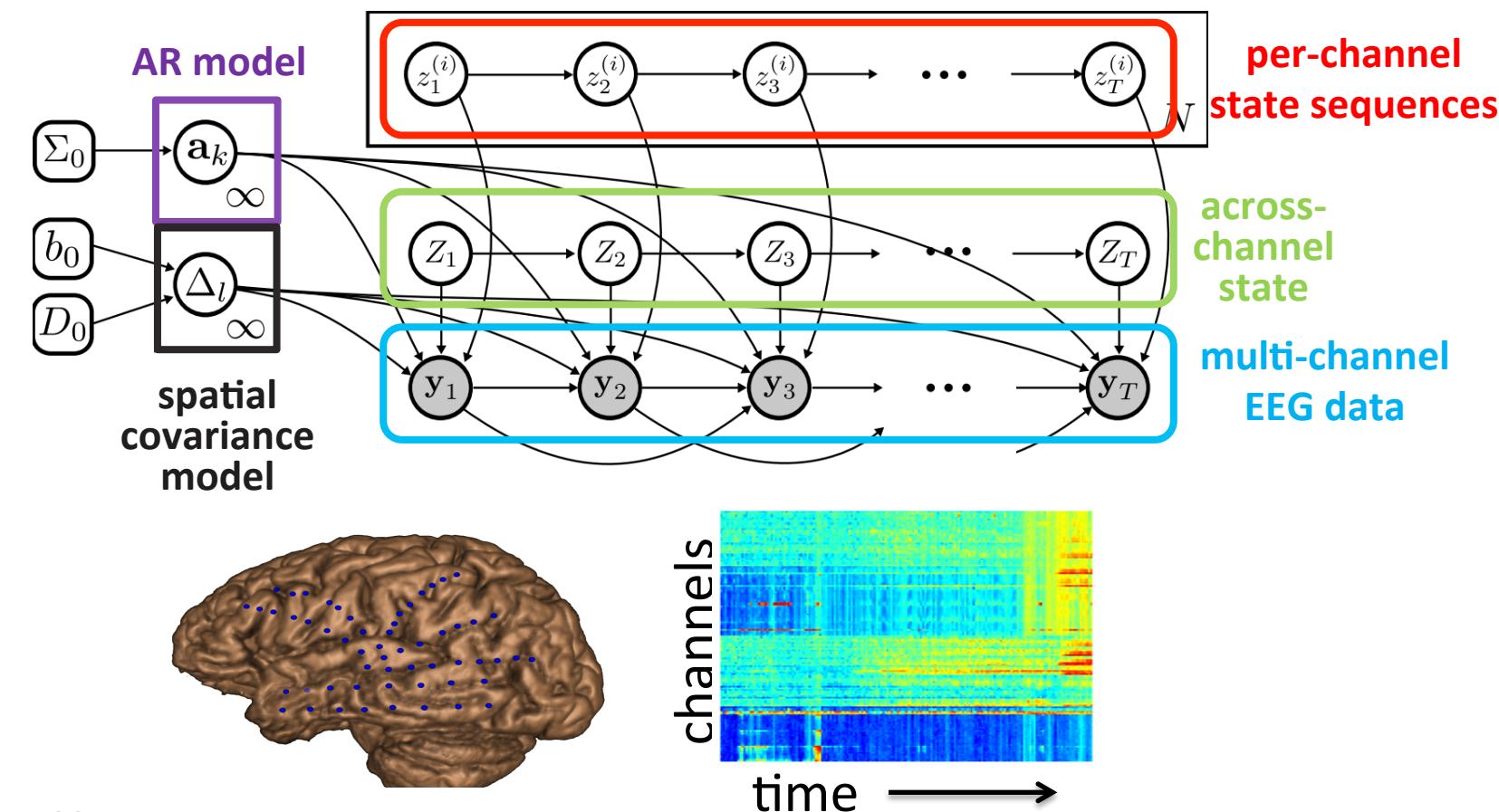
Open challenges: Scaling

Data is getting big...

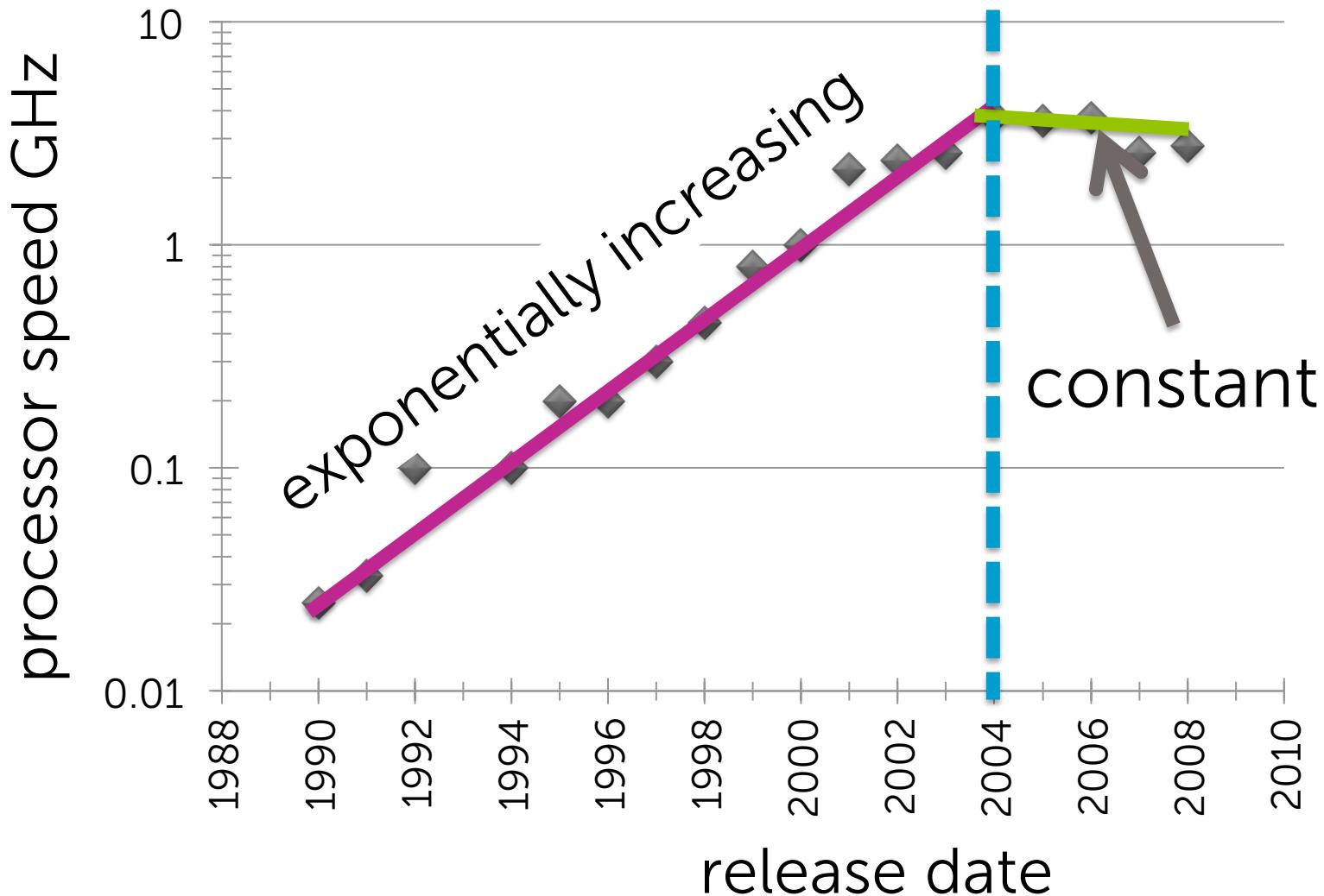


Open challenges: Scaling

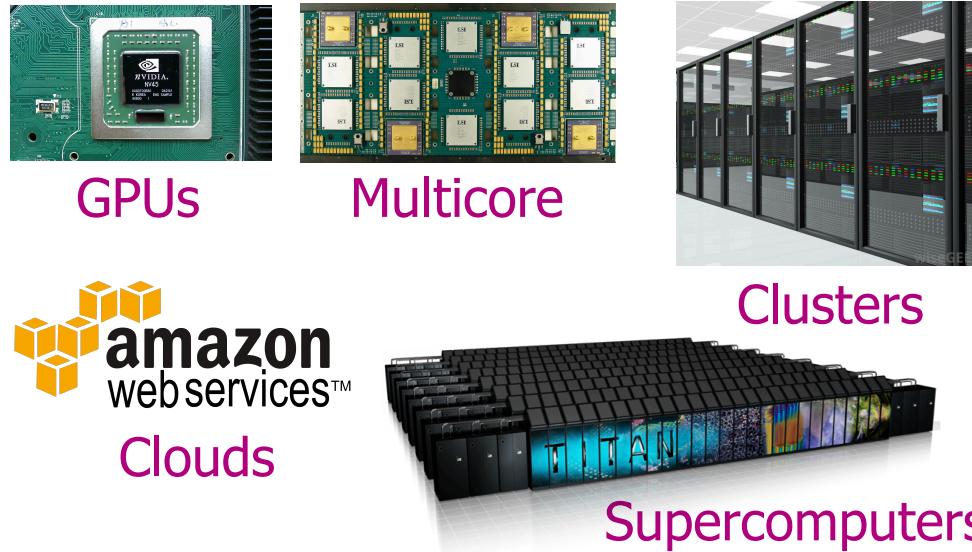
Concurrently, models are getting big...



CPUs stopped getting faster...



ML in the context of parallel architectures



But scalable ML in these systems is **hard**, especially in terms of:

1. Programmability
2. Data distribution
3. Failures

What's ahead in this specialization

2. Regression

Case study: Predicting house prices

Models

- Linear regression
- Regularization:
Ridge (L2), Lasso (L1)

Including many features:

- Square feet
- # bathrooms
- # bedrooms
- Lot size
- Year built
- ...



2. Regression

Case study: Predicting house prices

Algorithms

- Gradient descent
- Coordinate descent

$$\begin{aligned} \text{RSS}(\mathbf{w}_0, \mathbf{w}_1) = & \\ & (\$_{\text{house 1}} - [\mathbf{w}_0 + \mathbf{w}_1 \text{sq.ft.}_{\text{house 1}}])^2 \\ & + (\$_{\text{house 2}} - [\mathbf{w}_0 + \mathbf{w}_1 \text{sq.ft.}_{\text{house 2}}])^2 \\ & + (\$_{\text{house 3}} - [\mathbf{w}_0 + \mathbf{w}_1 \text{sq.ft.}_{\text{house 3}}])^2 \\ & + \dots \text{[include all houses]} \end{aligned}$$

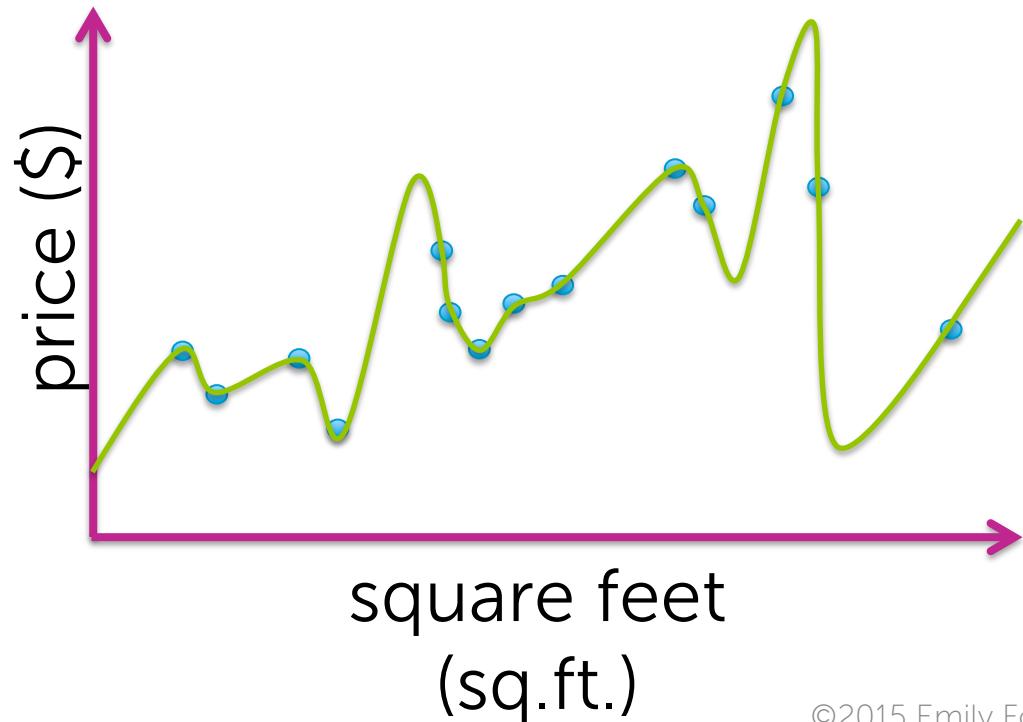
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2. Regression

Case study: Predicting house prices

Concepts

- Loss functions, bias-variance tradeoff, cross-validation, sparsity, overfitting, model selection

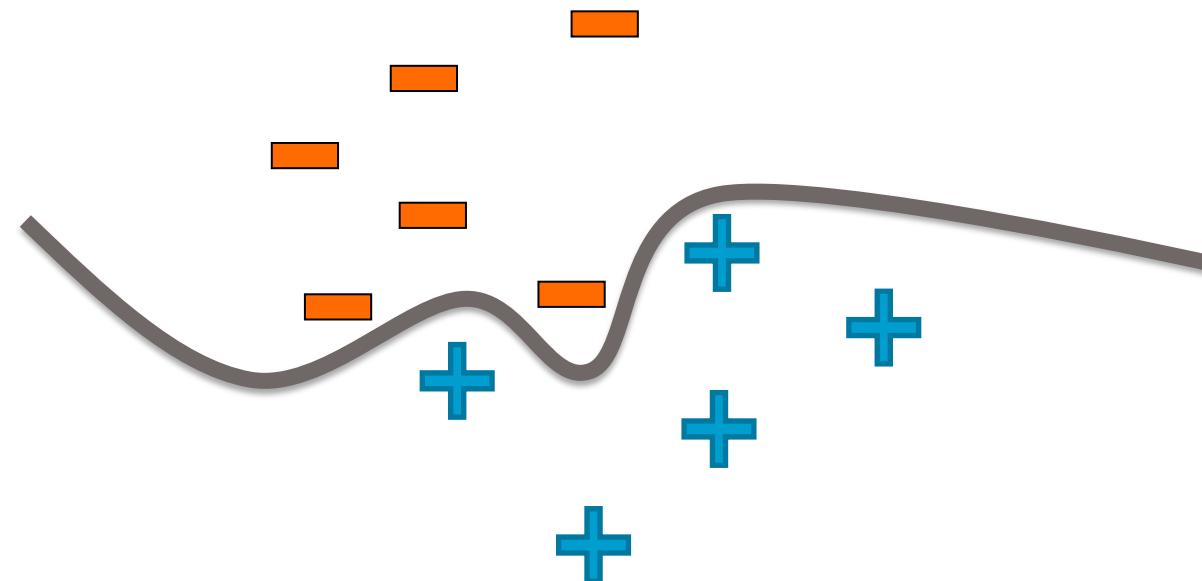


3. Classification

Case study: Analyzing sentiment

Models

- Linear classifiers
(logistic regression, SVMs, perceptron)
- Kernels
- Decision trees



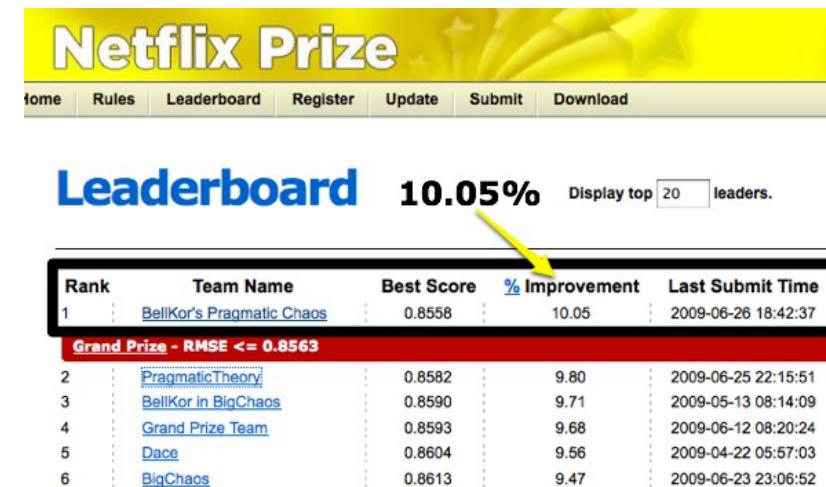
3. Classification

Case study: Analyzing sentiment

Algorithms

- Stochastic gradient descent
- Boosting

Squeezing last bit
of accuracy by
blending models



The screenshot shows the Netflix Prize Leaderboard. At the top, it displays "10.05%" with a yellow arrow pointing to the "% Improvement" column header. Below this, the top submission is listed:

Rank	Team Name	Best Score	% Improvement	Last Submit Time
1	BellKor's Pragmatic Chaos	0.8558	10.05	2009-06-26 18:42:37
Grand Prize - RMSE <= 0.8563				
2	PragmaticTheory	0.8582	9.80	2009-06-25 22:15:51
3	BellKor in BigChaos	0.8590	9.71	2009-05-13 08:14:09
4	Grand Prize Team	0.8593	9.68	2009-06-12 08:20:24
5	Dace	0.8604	9.56	2009-04-22 05:57:03
6	BigChaos	0.8613	9.47	2009-06-23 23:06:52

3. Classification

Case study: Analyzing sentiment

Concepts

- Decision boundaries, MLE, ensemble methods, random forests, CART, online learning

★★★★★ 7/21/2015

This is probably my favorite place to eat Japanese in Seattle. My boyfriend and I ordered nigiri of scallop, Japanese snapper (seasonal), and the agedashi tofu and 2 special rolls. I would skip the special rolls, because the nigiri and sashimi cuts is where this place excels. The tofu, as recommended by other Yelpers was amazing. It's more chewy and the sauce/gravy is the perfect amount of flavor for the delicate tofu.

★★★★★ 6/11/2015

Dining here at the sushi bar made me feel like sitting front row to an amazing performance. We didn't have resos, banged down to the ID after work, got here breathlessly at 5:10pm, and got the last two seats in the place.

★★★★★ 6/9/2015

I came here having high expectations due to the reviews of this place, but i was bit disappointed. The restaurant is small so do make reservations when you come here. Dishes cost from \$4-26 each and dishes are small.

Time

4. Clustering & Retrieval

Case study: Finding documents

Models

- Nearest neighbors
- Clustering, mixtures of Gaussians
- Latent Dirichlet allocation (LDA)



SPORTS



WORLD NEWS



ENTERTAINMENT



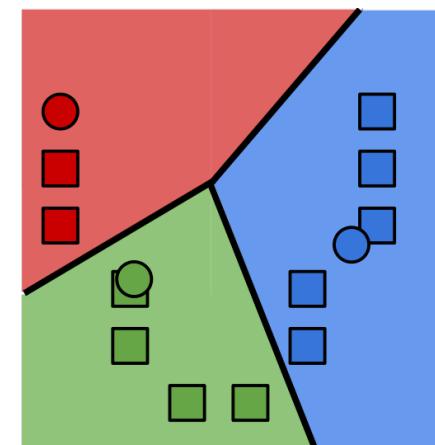
SCIENCE

4. Clustering & Retrieval

Case study: Finding documents

Algorithms

- KD-trees, locality-sensitive hashing (LSH)
- K-means
- Expectation-maximization (EM)



4. Clustering & Retrieval

Case study: Finding documents

Concepts

- Distance metrics, approximation algorithms, hashing, sampling algorithms, scaling up with map-reduce



1 0 0 0 5 3 0 0 1 0 0 0 0

$$1^*3 + 5^2 = 13$$

3 0 0 0 2 0 0 1 0 1 0 0 0



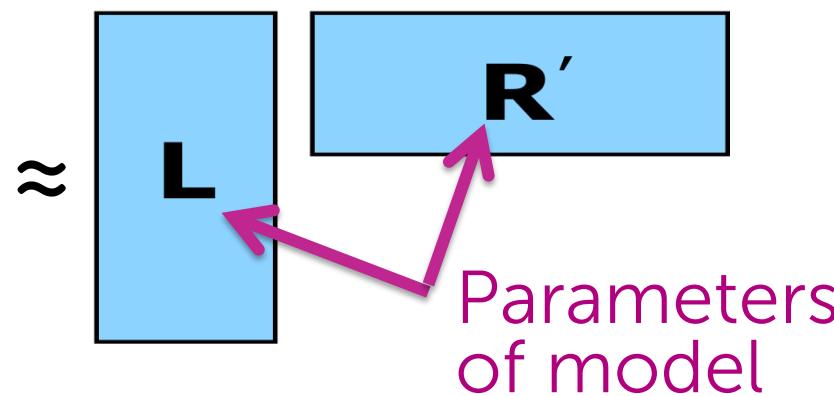
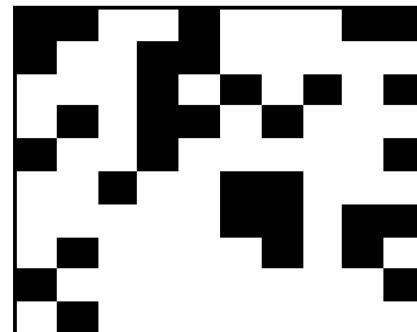
5. Recommender Systems & Dimensionality

Reduction *Case study: Recommending Products*

Models

- Collaborative filtering
- Matrix factorization
- PCA

Rating =



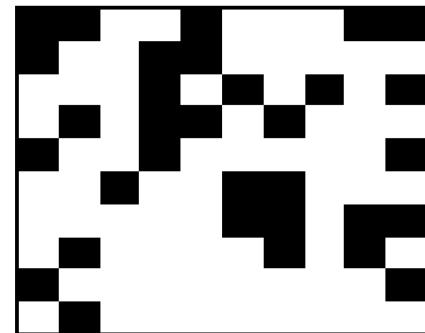
5. Matrix Factorization & Dimensionality Reduction

Case study: Recommending Products

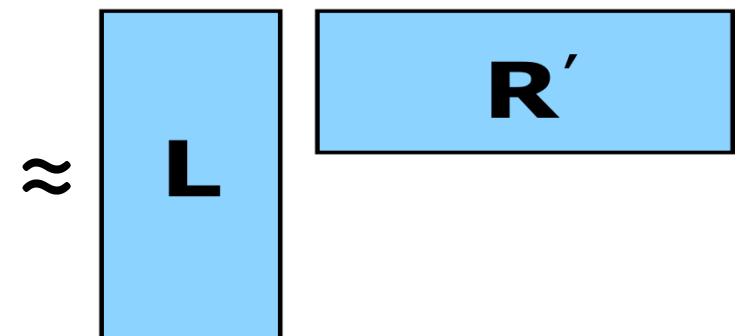
Algorithms

- Coordinate descent
- Eigen decomposition
- SVD

Rating =



Form estimates
 \hat{L}_u and \hat{R}_v

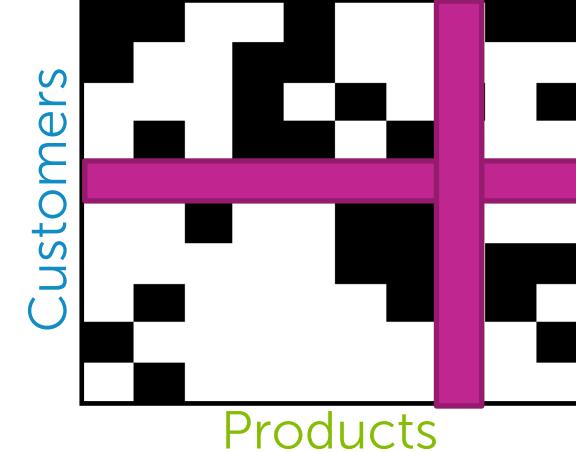
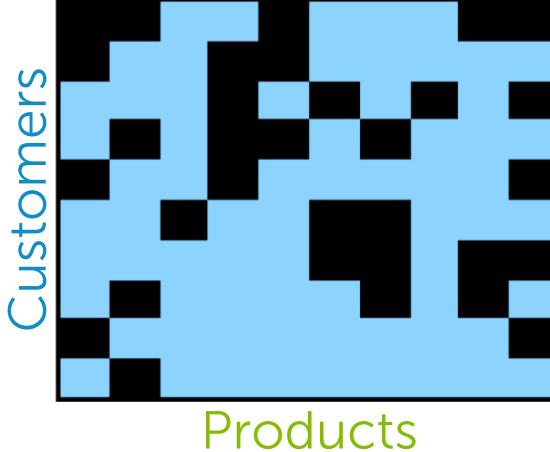


5. Matrix Factorization & Dimensionality Reduction

Case study: Recommending Products

Concepts

- Matrix completion, eigenvalues, random projections, cold-start problem, diversity, scaling up



6. Capstone: *Build and deploy an intelligent application with deep learning*

