Four Common Problems with Recommenders

And How to Address Them

The Problems

1. *Wrong Metric*
2. *Cold Start Problem*
3. *Difficulty Utilizing All Useful Data*
4. *Speed and Stability*

Sum Squared Errors Not Right Metric When Recommending Small Subset of Items

	True	Model A Pred	Model B Pred
Item 1	5	3	5
Item 2	3	3	3
Item 3	3	3	3
Item 4	3	3	1
Item 5	3	3	1
Item 6	2	4	2

Metrics Solutions

- *Alternative metrics*
  - *Average of Top N Recommendations*
  - *Objective function asymmetries*
    - *Account for different costs for different errors*

Cold Start Problem

Recommendations for new people or items are typically bad

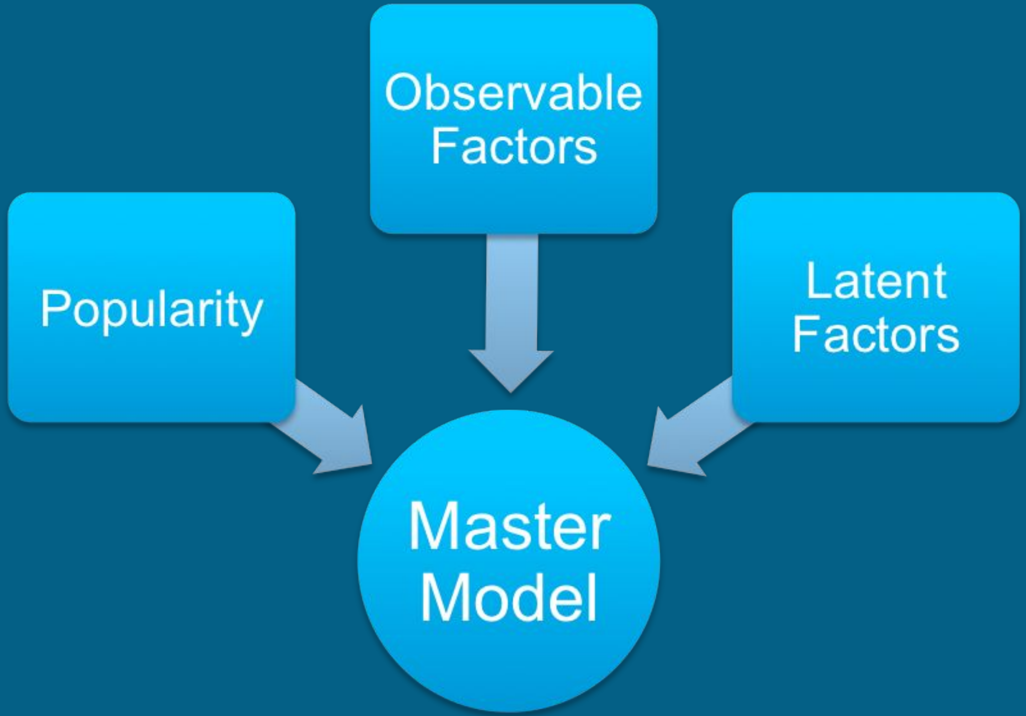
Cold Starts Problems in Various Recommender Systems

Most Affected
- Item-Item

Moderately Affected
- Latent Factors (SVD)

Least Affected
- Observable factors
- Popularity

Address Cold-Starts Without Sacrificing the Rest of Your Model



- Master model can use weighted average or switching
- Commonly solved with UI/UX rather than data science

What Predictive Data Do We Have That Factorization Isn't Using

What Predictive Data Do We Have That Factorization Isn't Using

- Average Ratings for Each User or Item (biases)
- Known Item Characteristics
- Known User Characteristics
- Implicit Feedback

Integrating Known Item Characteristics

Factorization Feature

Item Matrix

	Latent 1	Latent 2	Latent 3	Observed 1	Observed 2
Item A	?	?	?	1	3
Item B	?	?	?	0	0
Item C	?	?	?	1	5

User Taste Matrix

	Latent 1	Latent 2	Latent 3	Observed 1	Observed 2
Al	?	?	?	?	?
Betty	?	?	?	?	?
Carl	?	?	?	?	?

Implicit Feedback

SVD++

- The items a user has chosen to purchase/rate tells us about their tastes.

Basic Factorization w/ Bias

$$\hat{r}_{ui} = b_{ui} + p_u^T q_i$$

SVD++

$$\hat{r}_{ui} = b_{ui} + q_i^T \left(p_u + |\mathrm{N}(u)|^{-\frac{1}{2}} \sum_{j \in \mathrm{N}(u)} y_j \right)$$

Execution Speed Tips

Serialize The Model	• Optimize from near the optimum • Good practice in general
Vectorize Operations	• Language dependent • Important in Python
Switching Models	• Skip unnecessary work
Work in Batches	• Benefits from understanding usage patterns

Another Take on Speed / Stability

Spark MLlib

GraphLab

Spark and GraphLab

Simple API

- DataFrame objects
- Familiar modeling API

Scalable

- Built for distributed computing
- Fast

Tested

- Reliability
- Documentation

```python
from pyspark.mllib.recommendation import ALS, MatrixFactorizationModel, Rating

# Load and parse the data
data = sc.textFile("data/mllib/als/test.data")
ratings = data.map(lambda l: l.split(',')).map(lambda l: Rating(int(l[0]), int(l[1]), float(l[2])))

# Build the recommendation model using Alternating Least Squares
rank = 10
numIterations = 20
model = ALS.train(ratings, rank, numIterations)

# Evaluate the model on training data
testdata = ratings.map(lambda p: (p[0], p[1]))
predictions = model.predictAll(testdata).map(lambda r: ((r[0], r[1]), r[2]))
ratesAndPreds = ratings.map(lambda r: ((r[0], r[1]), r[2])).join(predictions)
MSE = ratesAndPreds.map(lambda r: (r[1][0] - r[1][1])**2).reduce(lambda x, y: x + y) / ratesAndPreds.count()
print("Mean Squared Error = " + str(MSE))

# Save and load model
model.save(sc, "myModelPath")
sameModel = MatrixFactorizationModel.load(sc, "myModelPath")
```

GraphLab. Recommender

```python
# The data needs to contain at least three columns: user, movie, and rating.
model = graphlab.recommender.create(data,
                                    user_id="user",
                                    item_id="movie",
                                    target="rating")
```

Methods

- Evaluate RMSE
- False positive and false negative rate at a given cutoff
- Predict
- Recommend
- Save

Should You Use Graphlab or Spark

Graphlab	• Appropriate for range of scales
MlLib	• Requires Spark • ALS solver at scale
Your Class	• Flexibility

Framework Conclusions

- Fast, reliable, well documented
- Harder to extend
- Only part of what you need