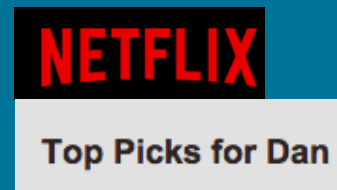
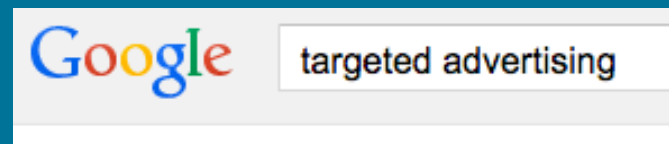
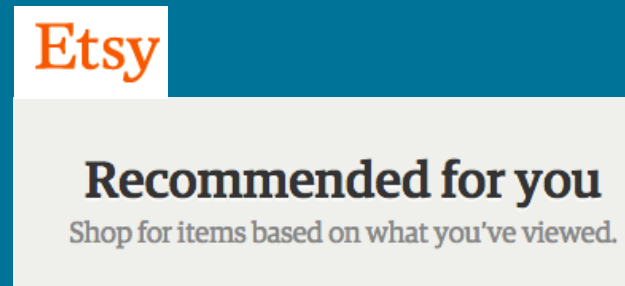
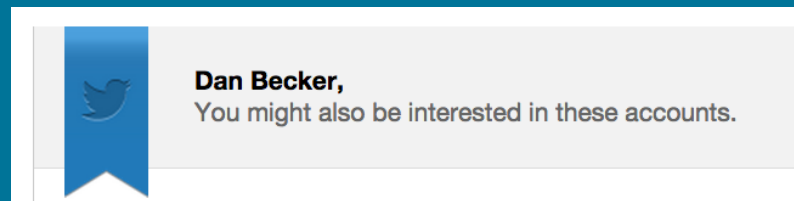
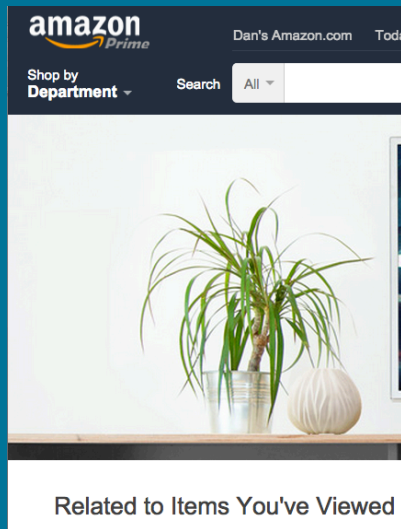


Recommender Systems

Dan Becker

Recommenders Everywhere



Answer This

What will this user

Buy

Click

Love

What You'll Learn

How to build, evaluate, deploy and improve models that make recommendations to users.

Example Data

User	Item				
	A	B	C	D	...
	Al	1	?	2	?
	Bob	?	2	3	4
	Cat	3	?	1	5
	Dan	?	2	?	?
	Ed	2	?	?	1
...					

Binary Data

User

Item					
	A	B	C	D	...
Al	0	1	0	1	
Bob	0	0	1	0	
Cat	0	1	1	1	
Dan	1	0	0	1	
Ed	0	1	0	0	
...					

Most Popular Techniques

Popularity

- Most viewed, most well-liked, etc
- Not customized to users

User-User

- Recommend items liked by users with similar ratings
- Computational challenges when more users than items

Item-Item

- Recommend items similar to what the current user rated favorably
- Covered in this lecture

Matrix Factorization Methods

- Estimate each user's underlying preferences for product characteristics
- Covered in next lectures

User Ratings as Vectors

User	Item				
		A	B	C	D
	Al	1	?	2	?
	Bob	?	2	3	4
	Cat	3	?	1	5

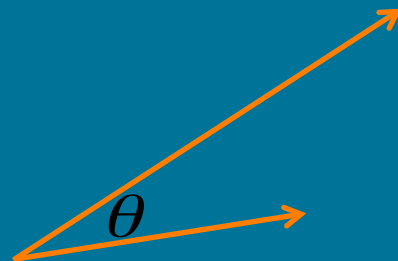
Item Ratings as Vectors

User

		Item			
		A	B	C	D
User	Al	1	?	2	?
	Bob	?	2	3	4
	Cat	3	?	1	5
	Dan	?	2	?	?
	Ed	2	?	?	1
	...				

Measuring Similarity

Metric Name	Useful For	Formula
Cosine	Numeric Ratings	$\frac{A \bullet B}{[A][B]}$
Jacard	Binary / Event Data	$\frac{A \cap B}{A \cup B}$



Measuring Similarity

Metric Name	Useful For	Formula
Cosine	Numeric Ratings	$\frac{A \bullet B}{[A][B]}$
Jacard	Binary / Event Data	$\frac{A \cap B}{A \cup B}$

Cosine Sim

$$sim(i, j) = \frac{\sum_{u \in U} (R_{u,i} - \bar{R}_i)(R_{u,j} - \bar{R}_j)}{\sqrt{\sum_{u \in U} (R_{u,i} - \bar{R}_i)^2} \sqrt{\sum_{u \in U} (R_{u,j} - \bar{R}_j)^2}}$$

Adjusted Cosine Sim

$$sim(i, j) = \frac{\sum_{u \in U} (R_{u,i} - \bar{R}_u)(R_{u,j} - \bar{R}_u)}{\sqrt{\sum_{u \in U} (R_{u,i} - \bar{R}_u)^2} \sqrt{\sum_{u \in U} (R_{u,j} - \bar{R}_u)^2}}$$

Item-Item Recommendation Algorithm

In The Middle of the Night

- Compute similarity metric for all pairs of items
- Create “neighborhood” of similar items for each item to rate

At Request Time

- Predict scores for candidate items

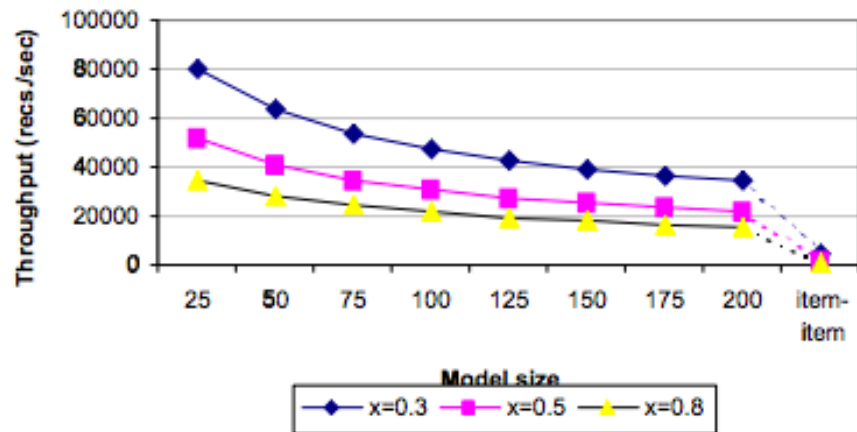
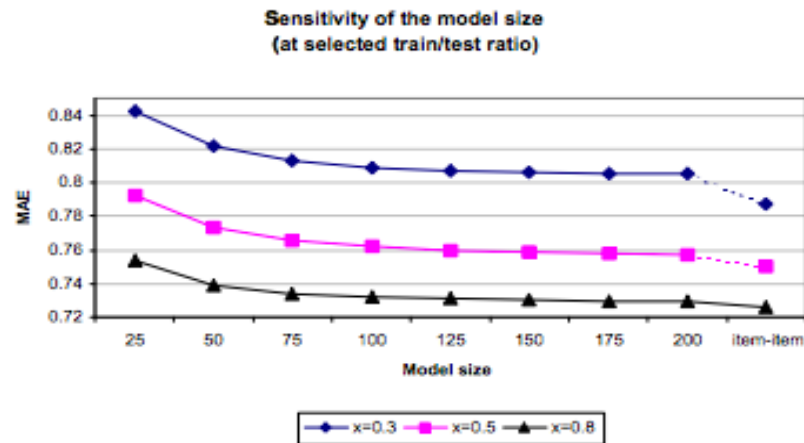
Item-Item Recommendation Algorithm

At Request Time

- Predict scores for candidate items

$$P_{u,i} = \frac{\sum_{\text{all similar items, } N} (s_{i,N} * R_{u,N})}{\sum_{\text{all similar items, } N} (|s_{i,N}|)}$$

Item-Item Recommendation Algorithm



Why Item-Item rather Than User- User

Caching

- Item correlations more stable

Similarity Calculation (Speed)

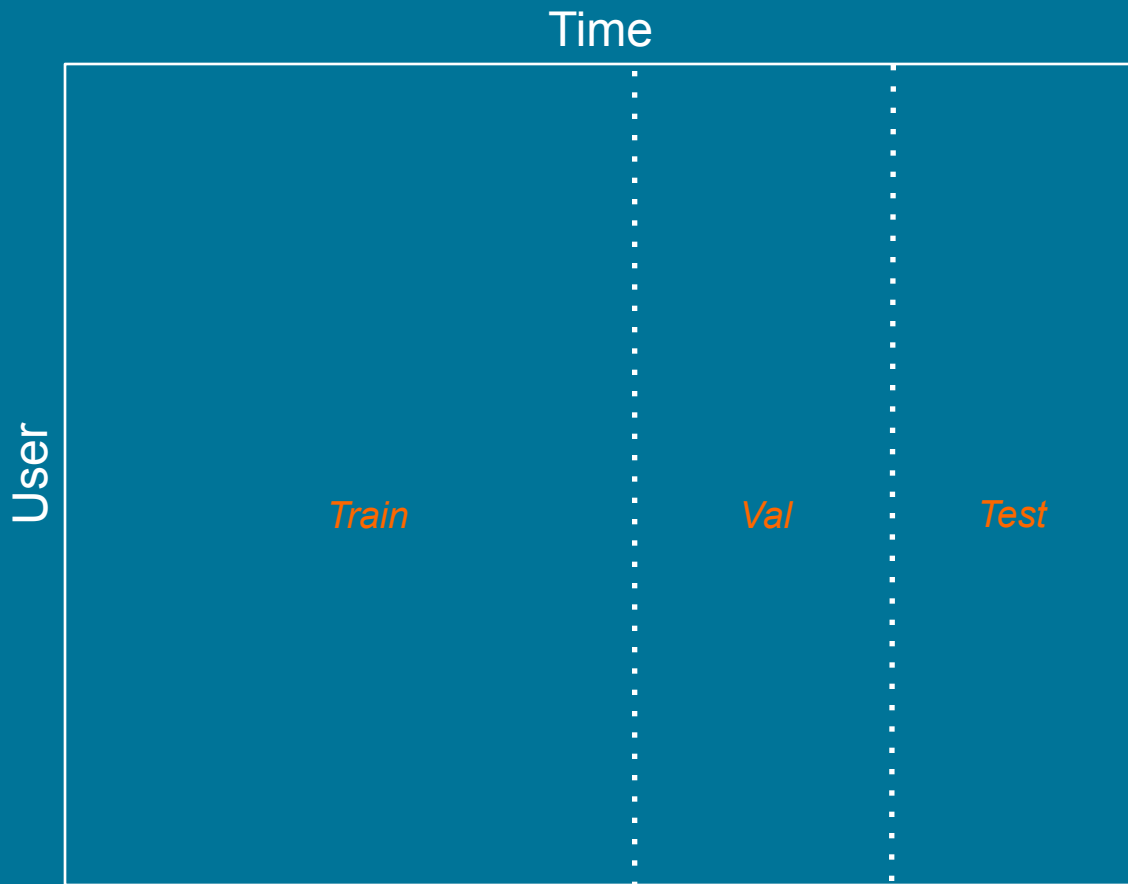
- Lower algorithmic complexity

Similarity Calculation (Quality)

- User-pairs with only 1 overlapping rating

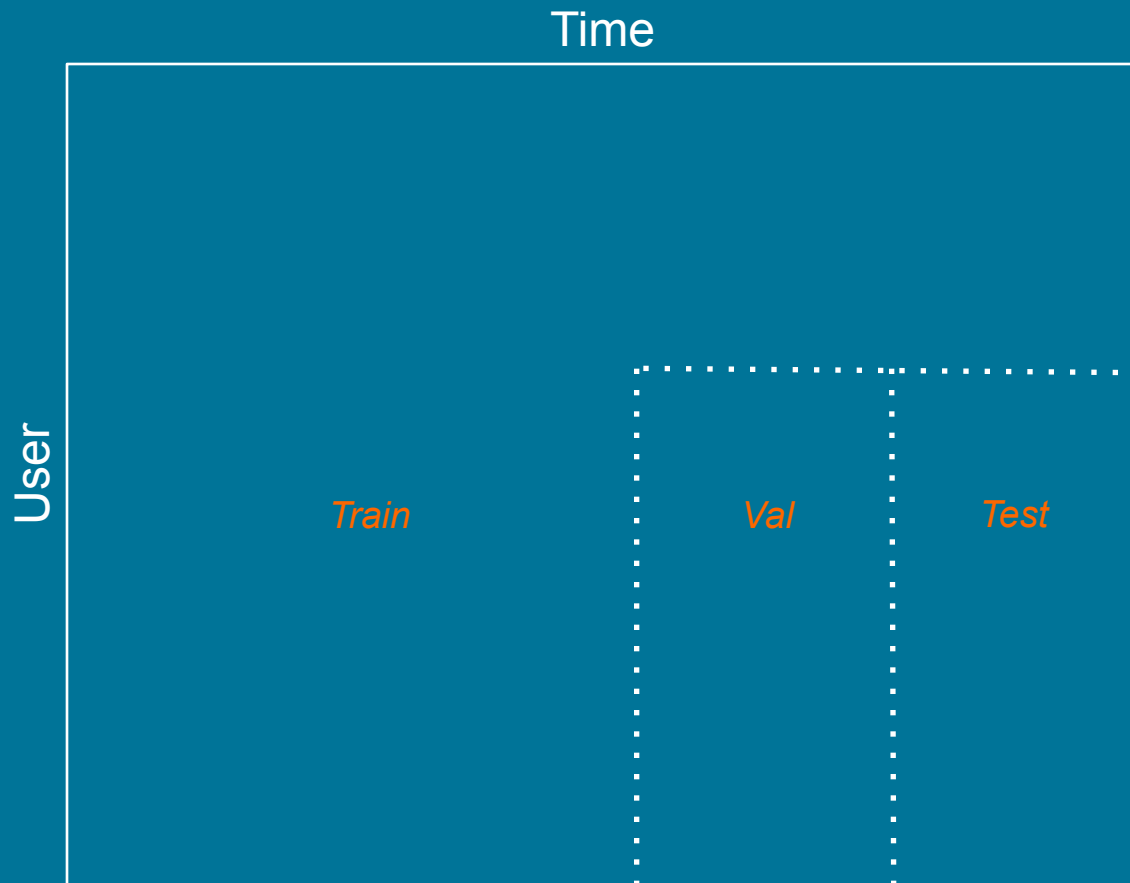
Validation Strategies

Simple Time-Based



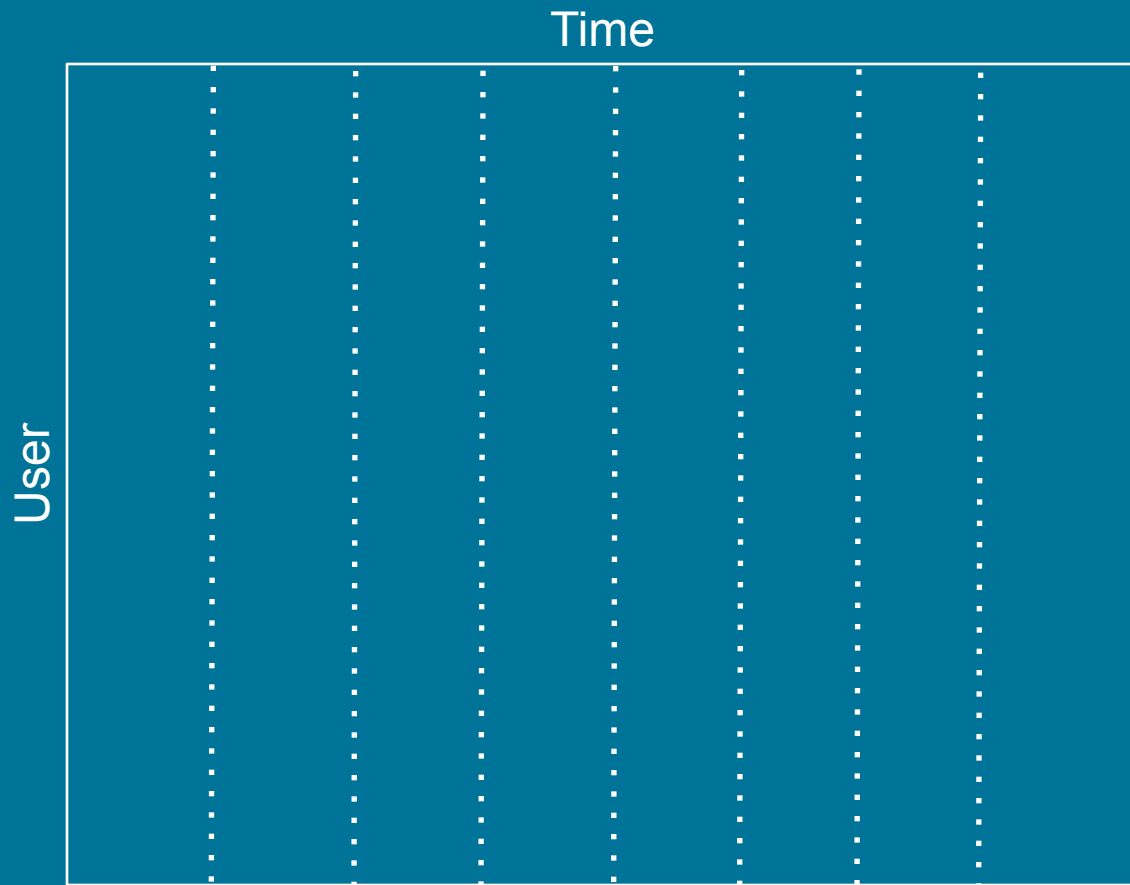
Validation Strategies

More Complex Time-Based

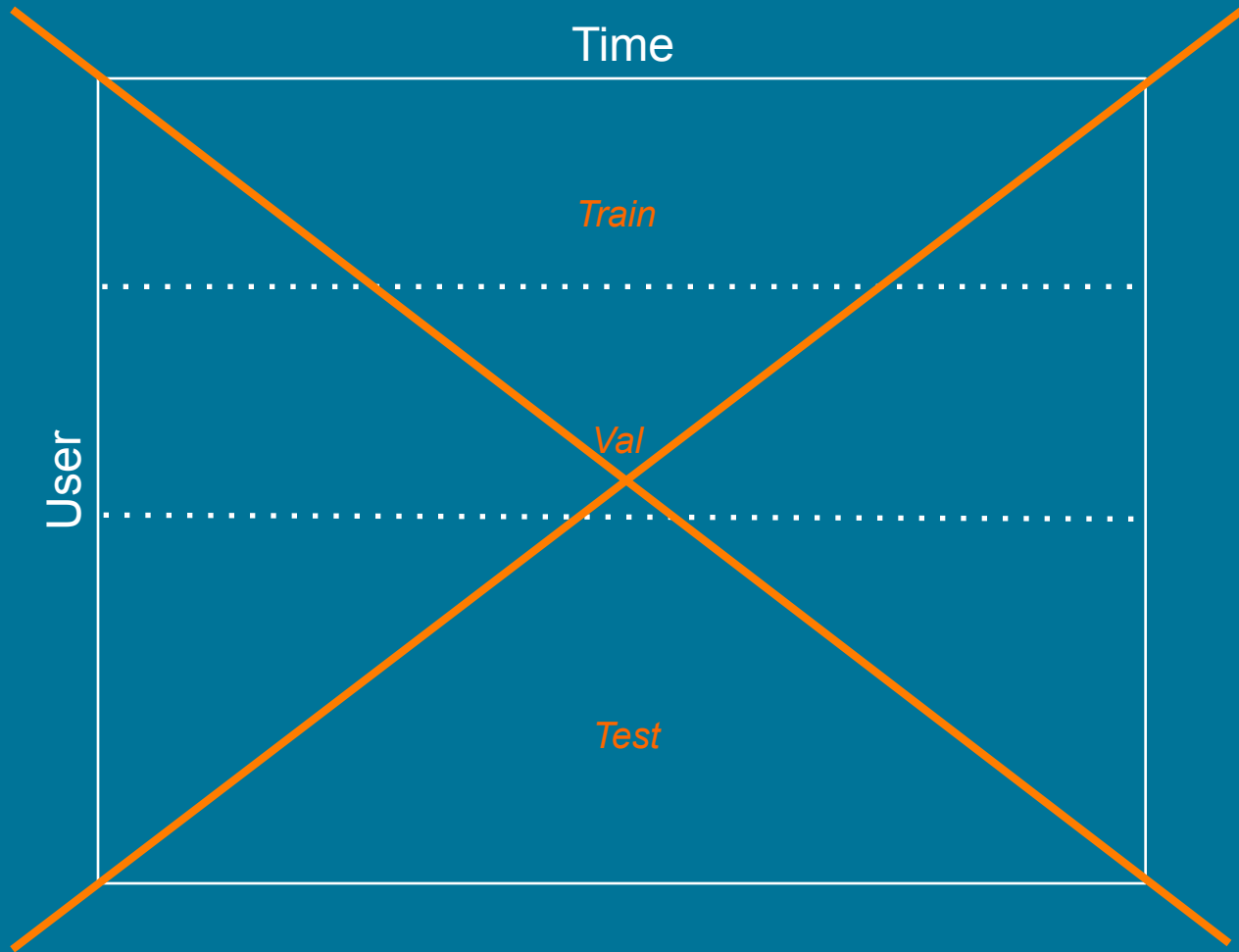


Validation Strategies

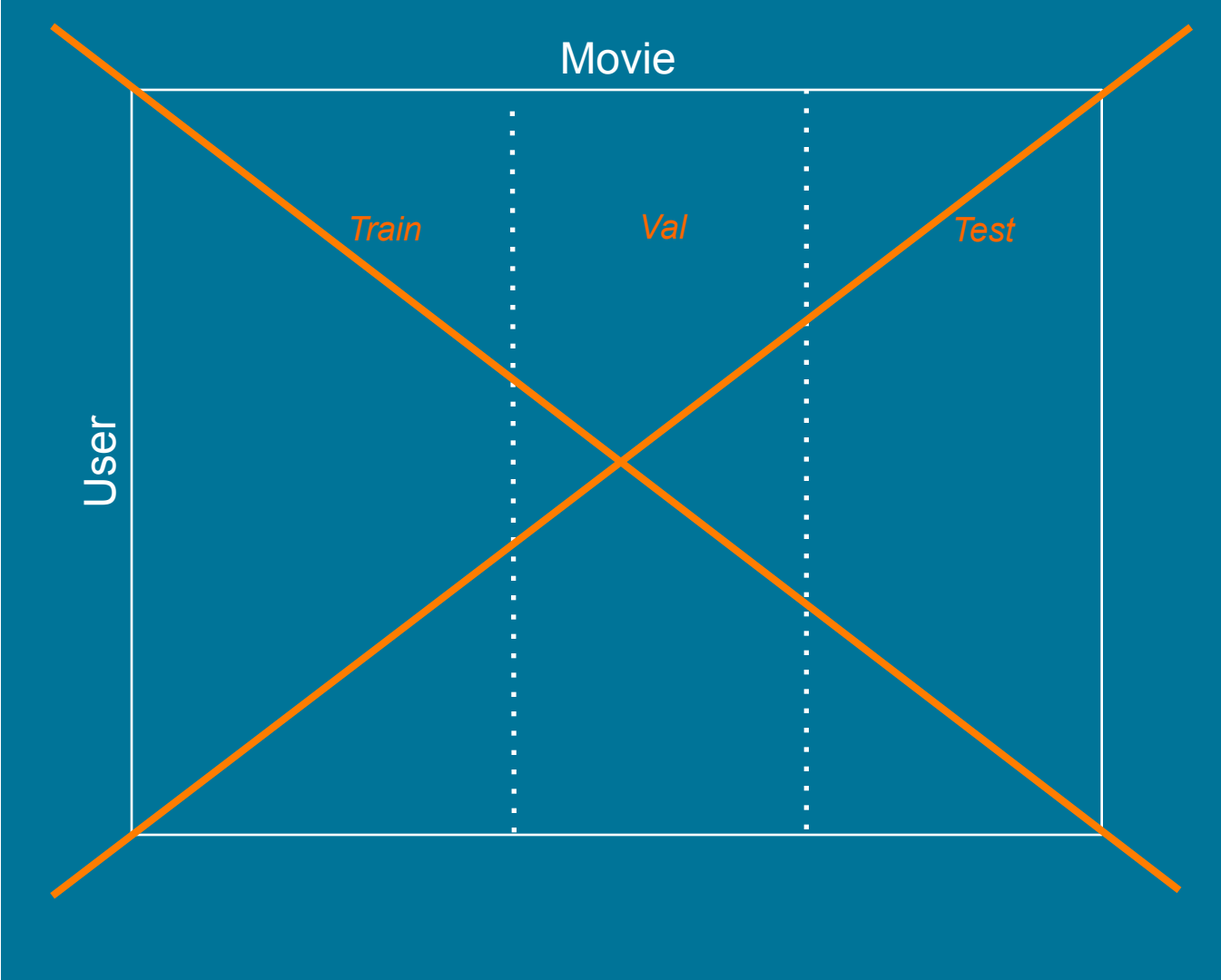
K-Fold



Thought Experiment: Why Doesn't This Work



Another Bad
Validation Strategy



Validation Strategies

Purely Random Holdout (Optionally K-fold)

