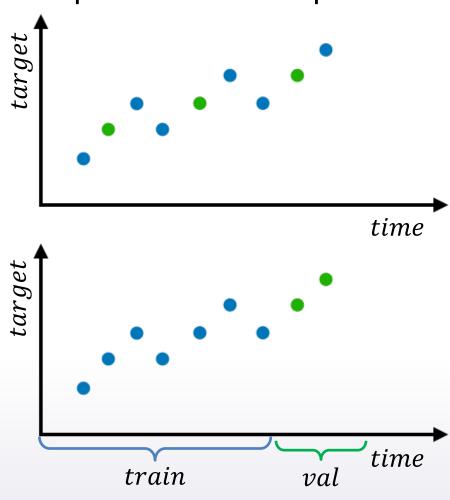
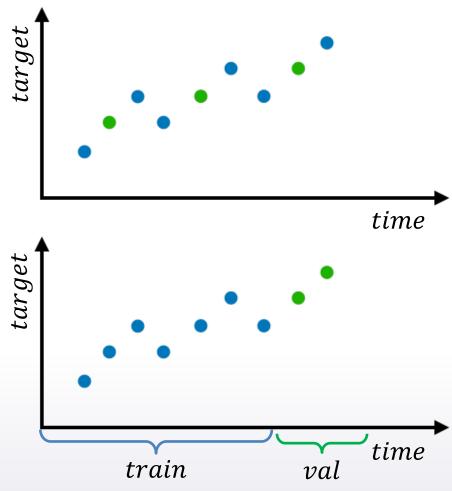
# Data splitting strategies

set up validation to replicate train/test split



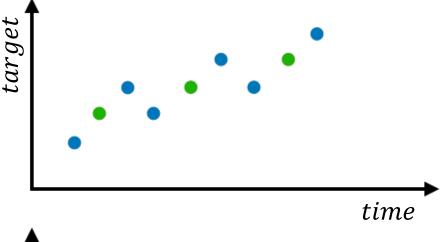
#### Important features:

Previous and next target values

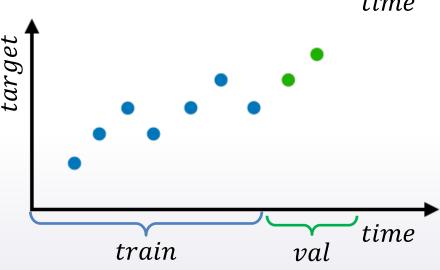


Important features:

Previous and next target values



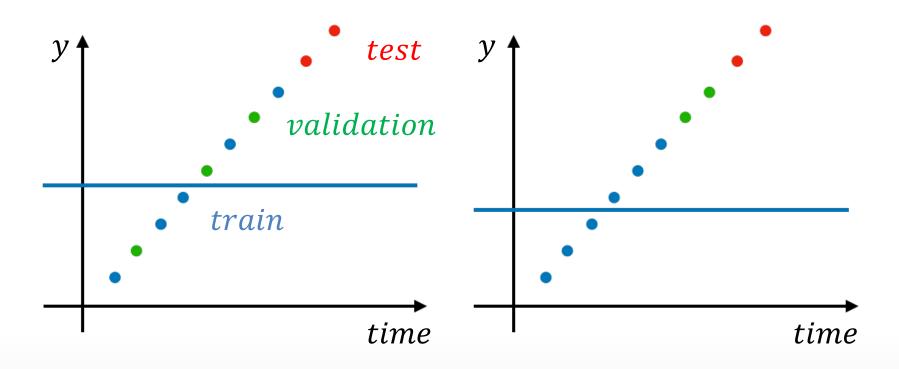
2. Time-based trend



#### **Question screen**

If we carefully generate features that are drawing attention to time-based patterns, will we get a reliable validation with a random-based split?

No



# Time-based splits

"Rossman Store Sales"

# **R®SSMANN**

"Grupo Bimbo Inventory Demand"



#### Important outcome

Different splitting strategies can differ significantly

- 1. in generated features
- 2. in a way the model will rely on that features
- 3. in some kind of target leak

- 1. Random, rowwise
- 2. Timewise
- 3. By id

- 1. Random, rowwise
- 2. Timewise
- 3. By id

the most common way of making a train/test split is to split data randomly by rows. This usually means that the rows are independent of each other.

- 1. Random, rowwise
- 2. Timewise
- 3. By id





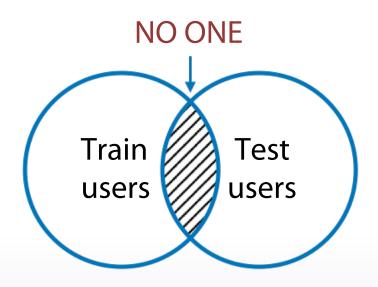
If we are to predict a number of customers for the shop for each day in the next week, we can came up with something like the number of customers for the same day in the previous week, or the average number of customers for the past month.

# Moving window

#### Moving window validation

week1	week2	week3	week4	week5	week6
	train		validation		
train validation					
train					validation

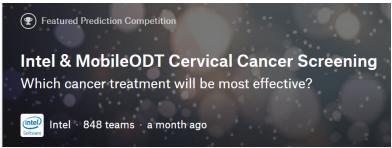
- 1. Random, rowwise
- 2. Timewise
- 3. By id



- 1. Random, rowwise
- 2. Timewise
- 3. By id





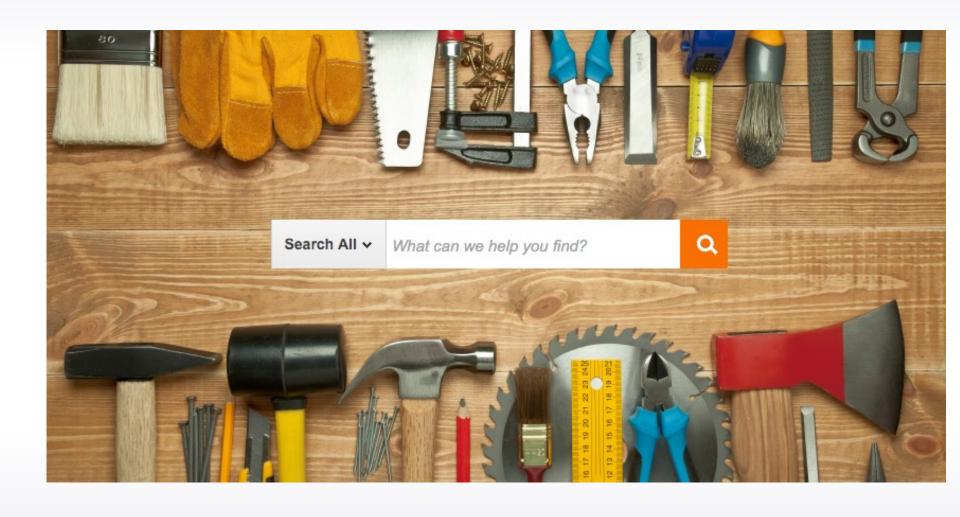


- 1. Random, rowwise
- 2. Timewise
- 3. By id
- 4. Combined





# Home Depot Product Search Relevance



#### Conclusion

- 1. In most cases data is split by
  - a. Row number
  - b. Time
  - c. Id
- Logic of feature generation depends on the data splitting strategy
- 3. Set up your validation to mimic the train/test split of the competition