Selecting Impactful Product Features

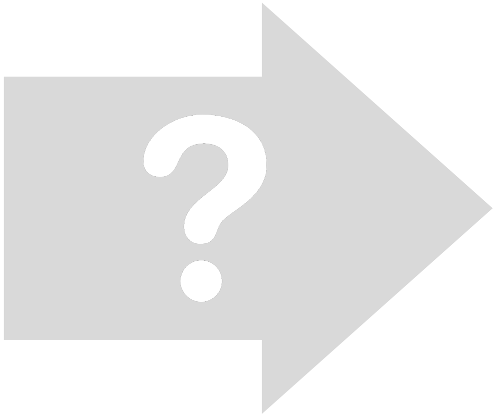
using statistics and machine learning

Ștefan Niculae

CONTENTS

PROBLEM STATEMENT

an application



make it better

PROBLEM STATEMENT

an application

?

make it better

make it more successful

PROBLEM STATEMENT

an application

?

make it better

make it more successful

increase the number of customers

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increase retention

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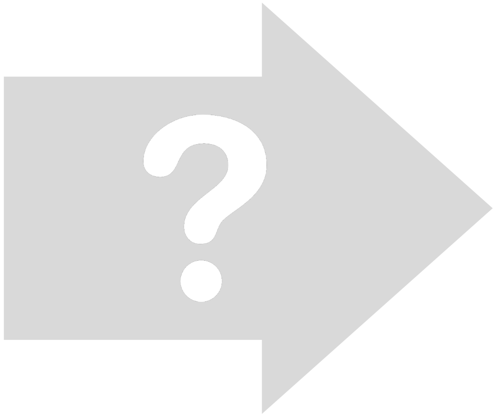

make it better

make it more successful

increase the number of customers

increase retention

features that impact retention the most

PROBLEM STATEMENT

an application

usage of an application

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Machine learning task!

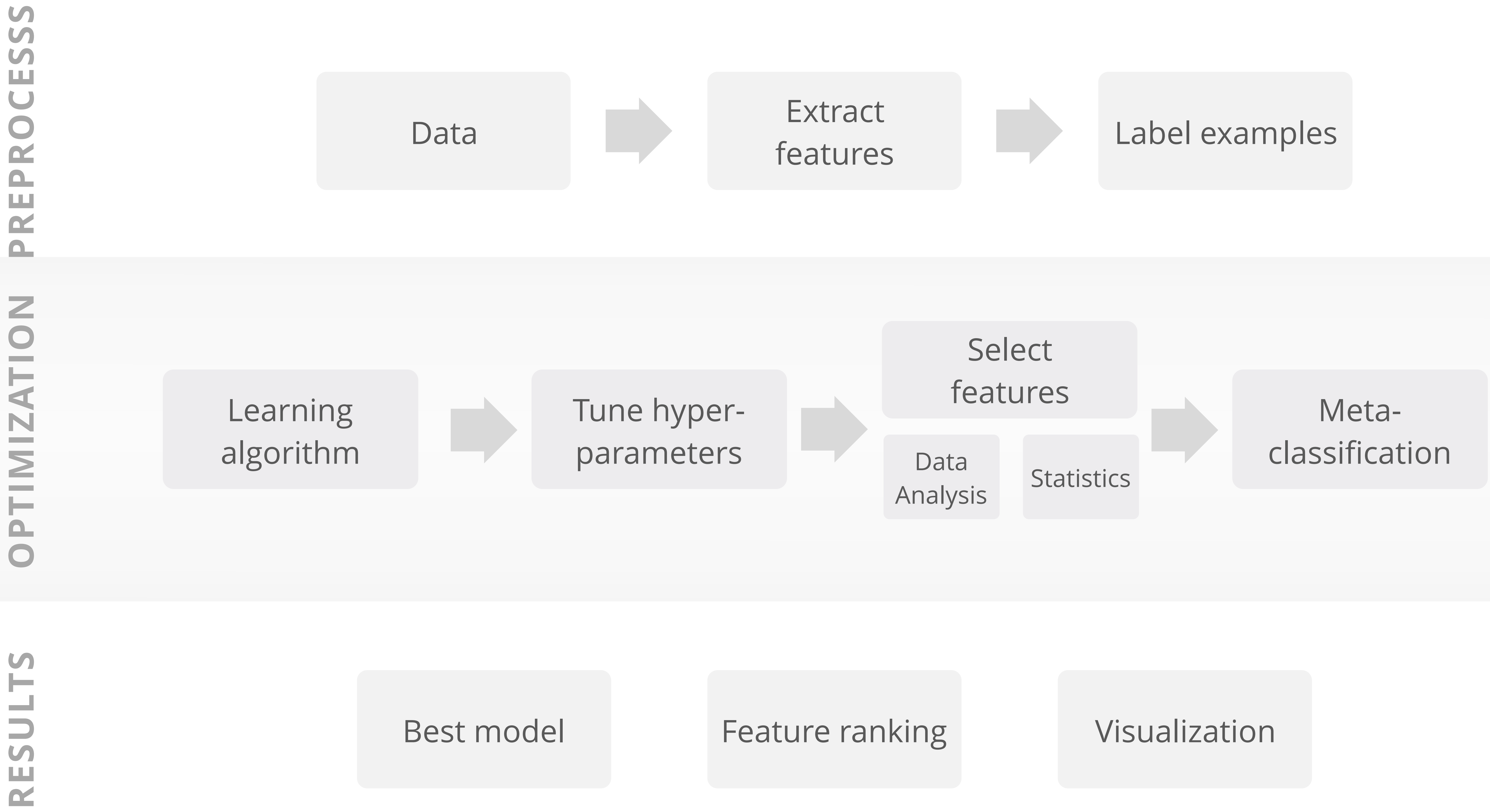
MACHINE LEARNING

train on some labeled examples,
then predict label for a new example

OUR PROBLEM

given a big dataset,
find most discriminatory features

OVERVIEW

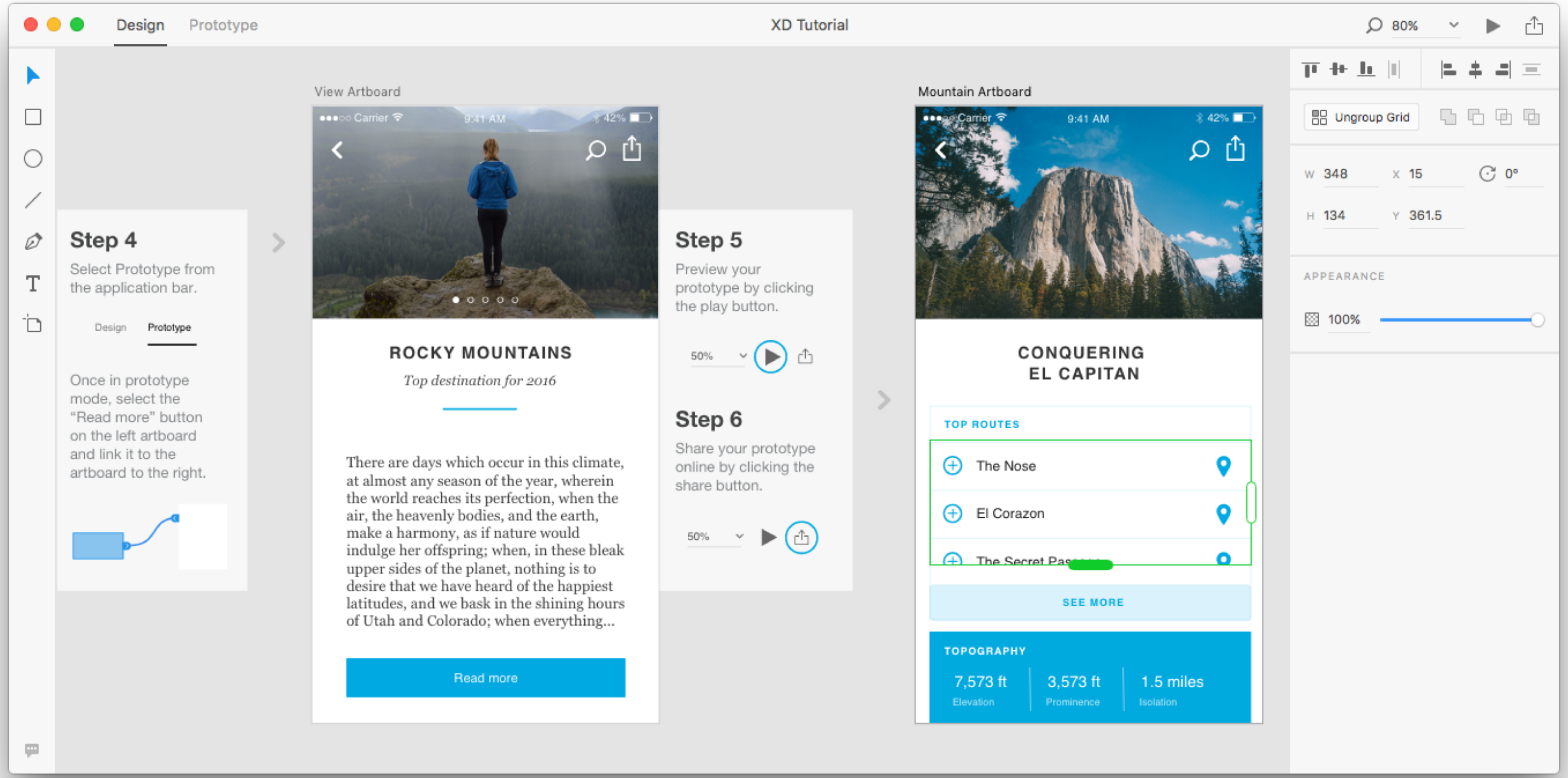

PREPROCESSS
Data
Extract features
Label examples
OPTIMIZATION
Learning algorithm
Tune hyper-parameters
Select features
Data Analysis
Statistics
Meta-classification
RESULTS
Best model
Feature ranking
Visualization

APPROACH

train a model,
it will understand data relationships.
ask it what features helped decide the most

more accurate model,
more valuable its opinion

THE APPLICATION



Adobe Experience Design

BEFORE LEARNING

Dataset → Features → Labels

Get a dataset containing relevant examples

Extract measurements to use for each user

Decide if each user is either a retainer or a churner

QUICK NUMBERS

43k	115k	4.8m
users	sessions	events

no outliers (98 quantile) or accidents (<15s)

EXTRACTED FEATURES

DOCUMENT
opened, created, saved
imported, exported, shared

DRAWS
rectangles, ellipses, lines, paths, text
artboards, repeat-grids, wires

HISTORICAL
total time, number of
launches, days span

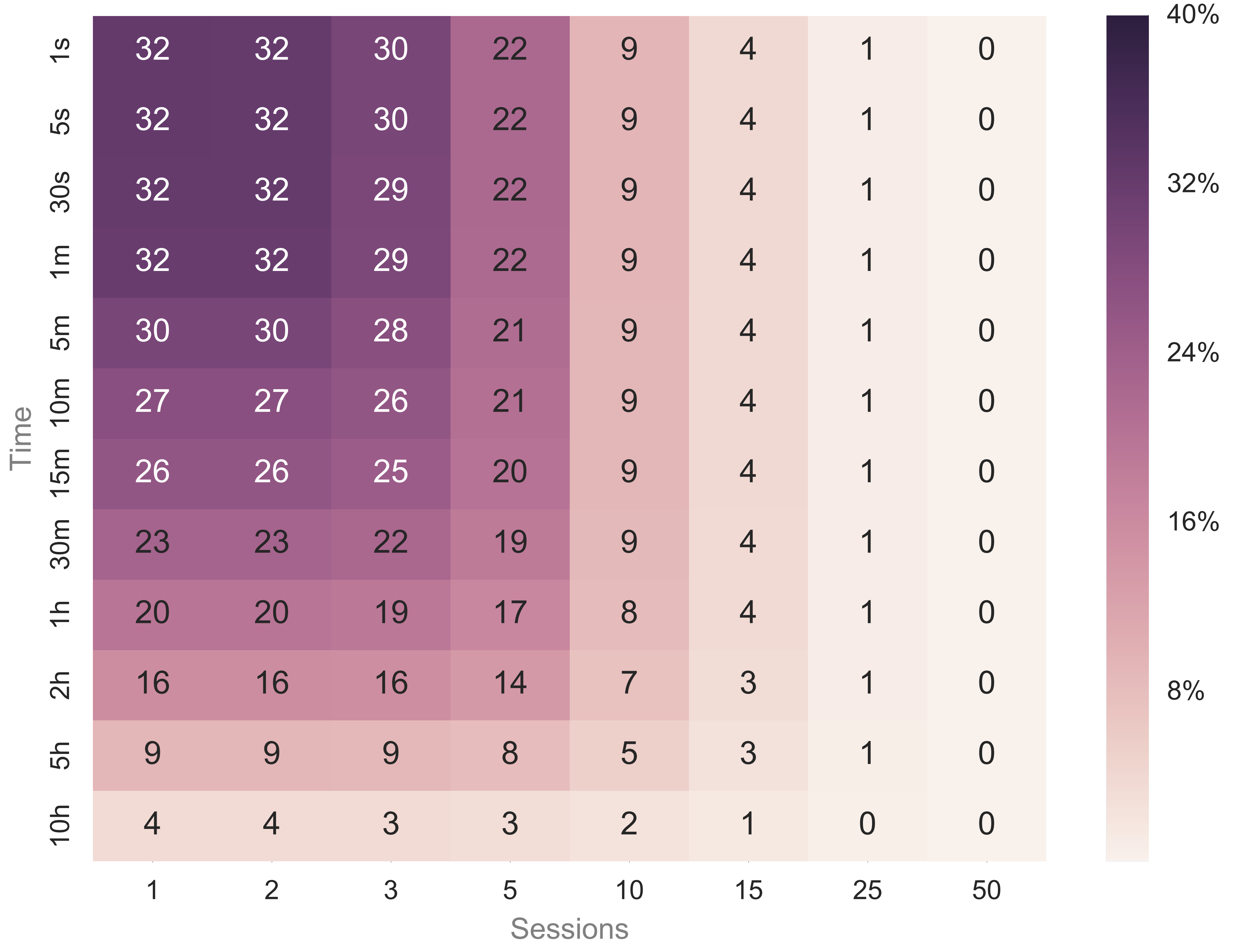
TIMES
in design, prototype, preview,
first session, action frequency

Counts ignore sequentiality.

Build action sequences

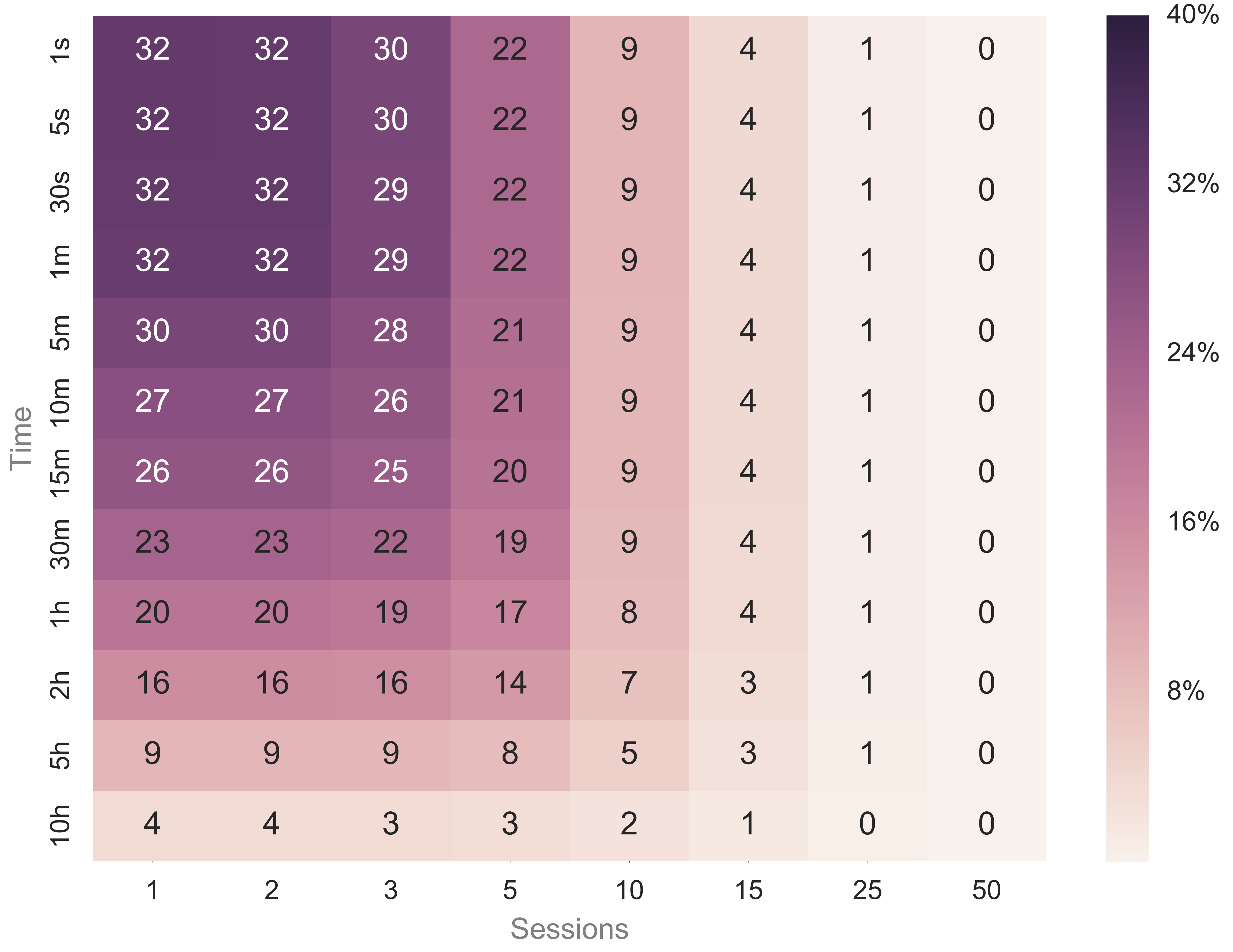
RETENTION DEFINITION

- time
- sessions
- days span



RETENTION DEFINITION

- time: 10m
- sessions: 3
- days span: 15



OPTIMIZE LEARNING

Algorithm → Hyper-parameters → Features

Algorithm

Chose a type of learner, and an actual algorithm

Hyper-parameters

Tune hyper-parameters for best generalization

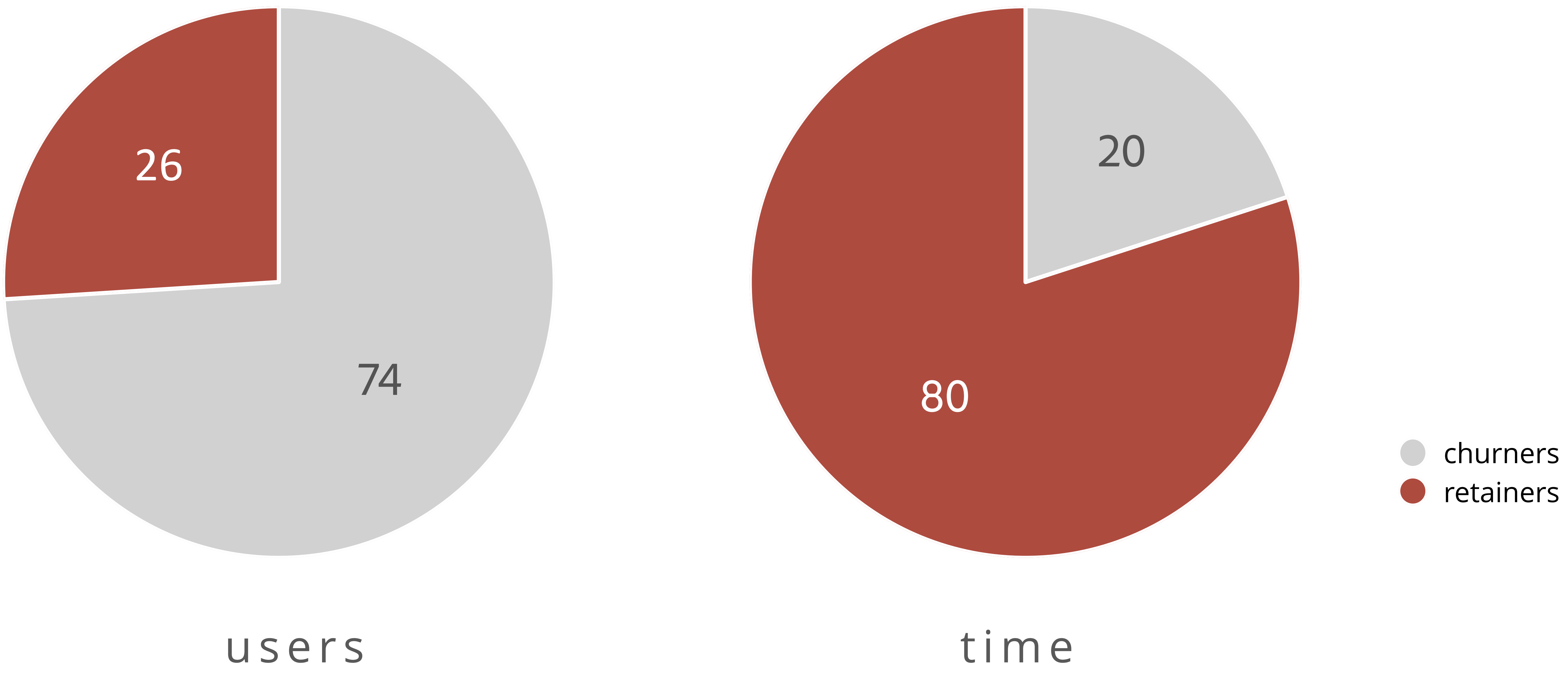
Features

Select the subset that brings the best performance

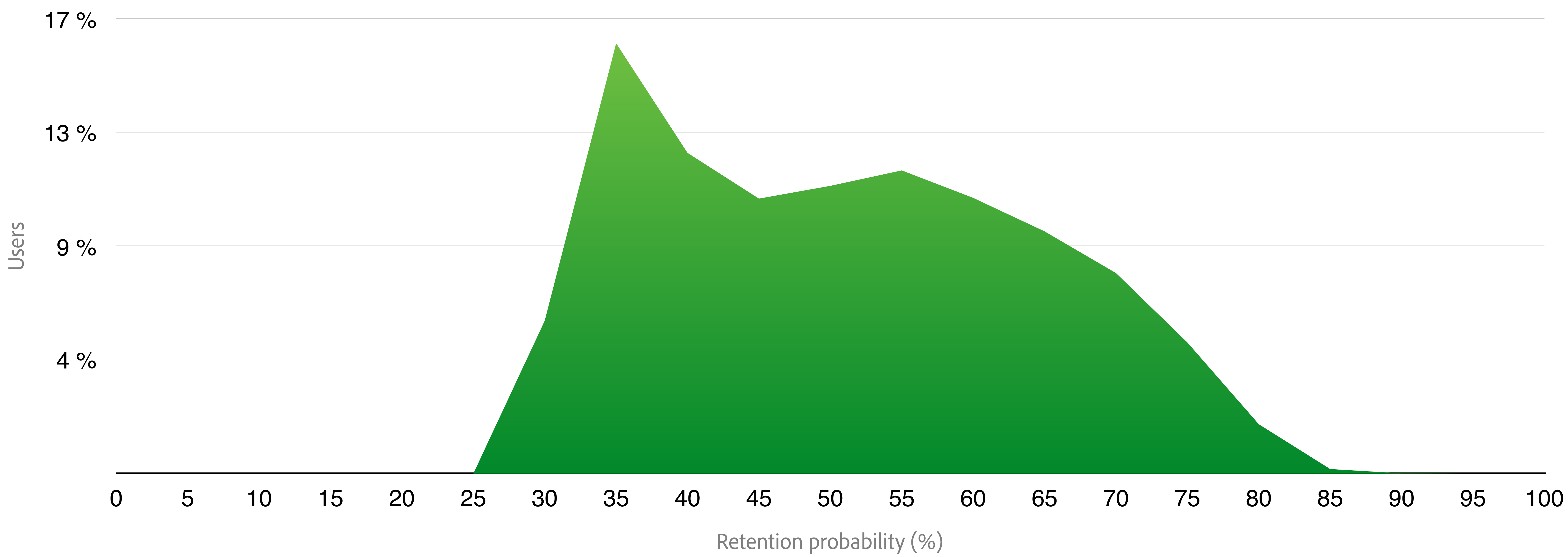
SELECTING A MODEL

- have to know the data beforehand
- need experience to pick,
- even experts need to rely on trial-and-error

PARETO IN PRACTICE



RETENTION DISTRIBUTION



LEARNING ALGORITHMS

- neural networks
- support vector machines
- decision tree forests
- naive bayes
- logistic regression
- gradient descent

- boosting
- bagging

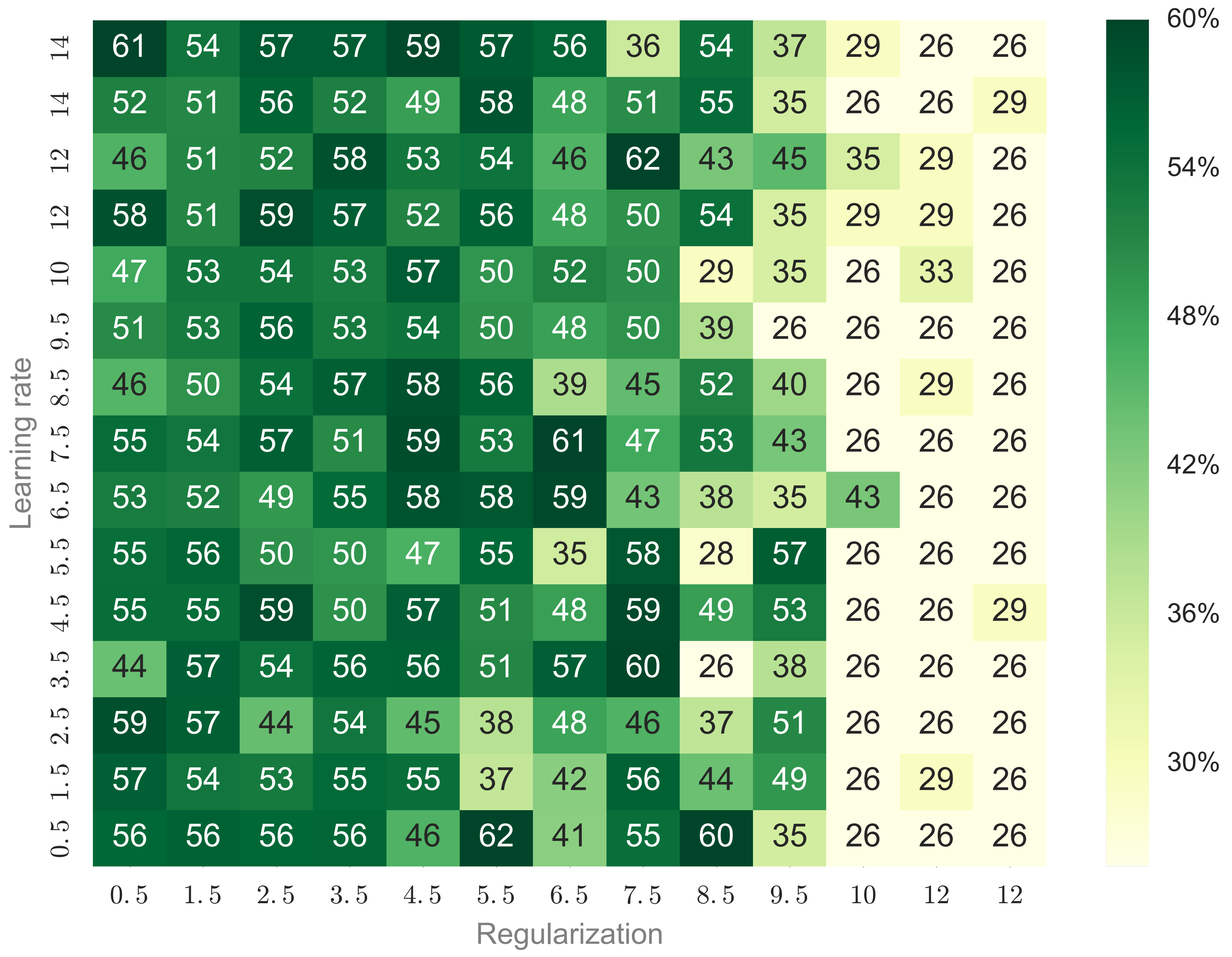
No free lunch theorem

HYPER-PARAMETERS

- models need to be tuned to be effective
- many have multiple hyper-parameters
- can't try every possible combination

$$\prod_{param} \#vals \times tt$$

HYPER-PARAMETER GRID



Horizon effect

HYPER-PARAM SEARCH

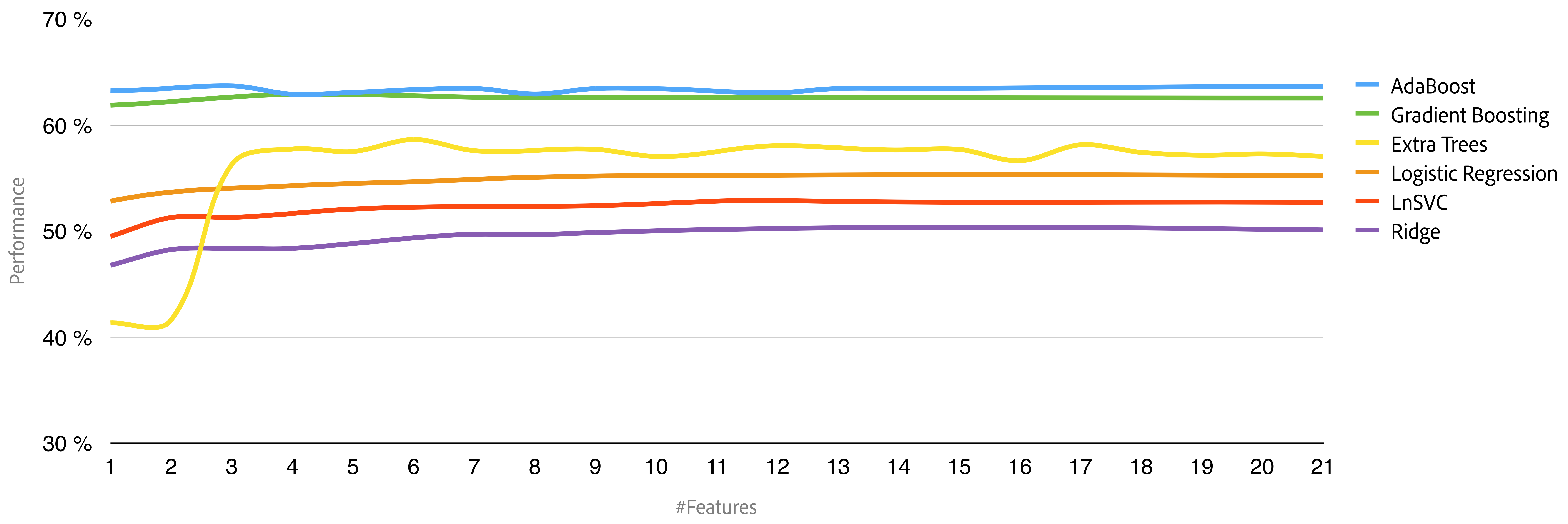
- grid search when model is fast
- randomized search instead
- and for continuous distributions as well

FEATURE SELECTION

- reduces complexity
- easier to interpret
- will learn relationships, not noise
- requires smaller training set

Curse of dimensionality

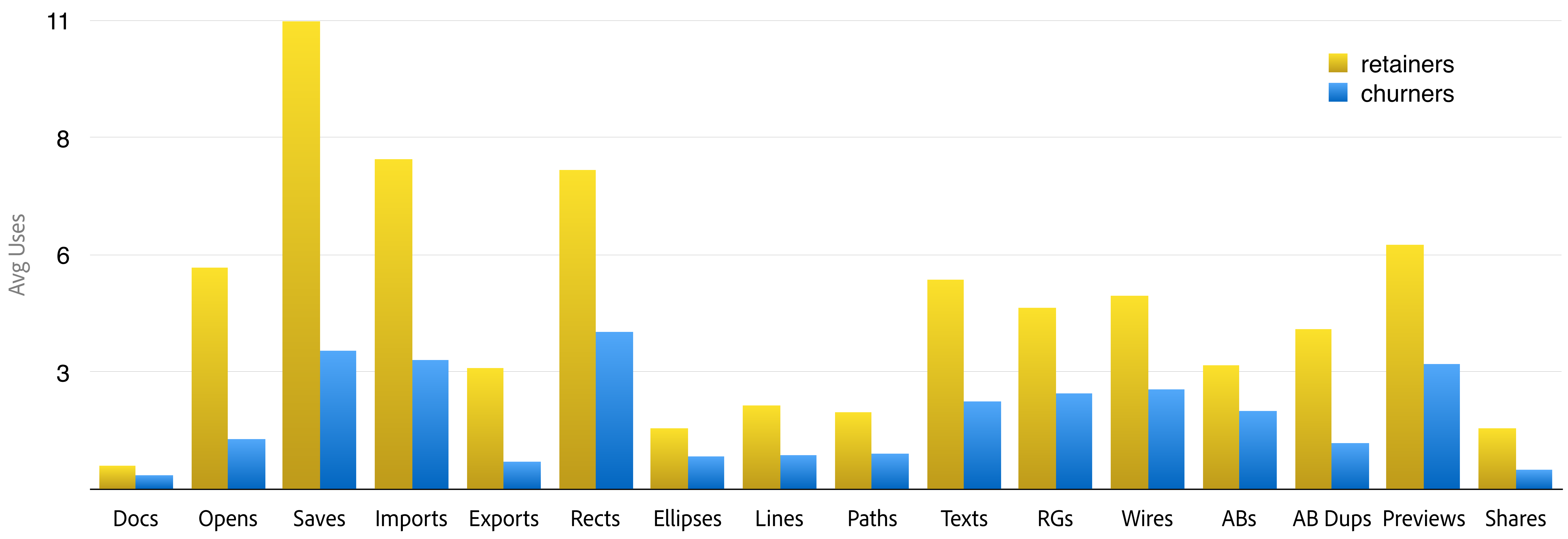
SUBSET PERFORMANCE



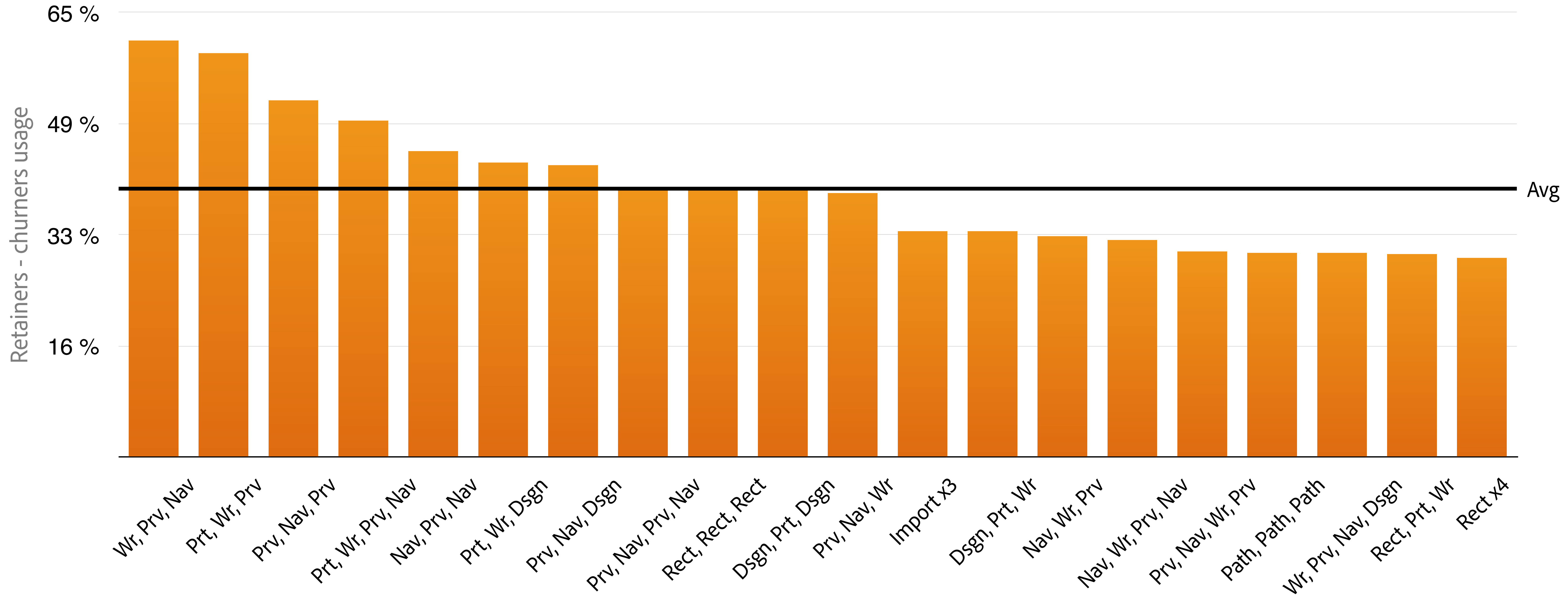
FS TECHNIQUES

- recursive feature elimination
- data analysis
- statistical methods

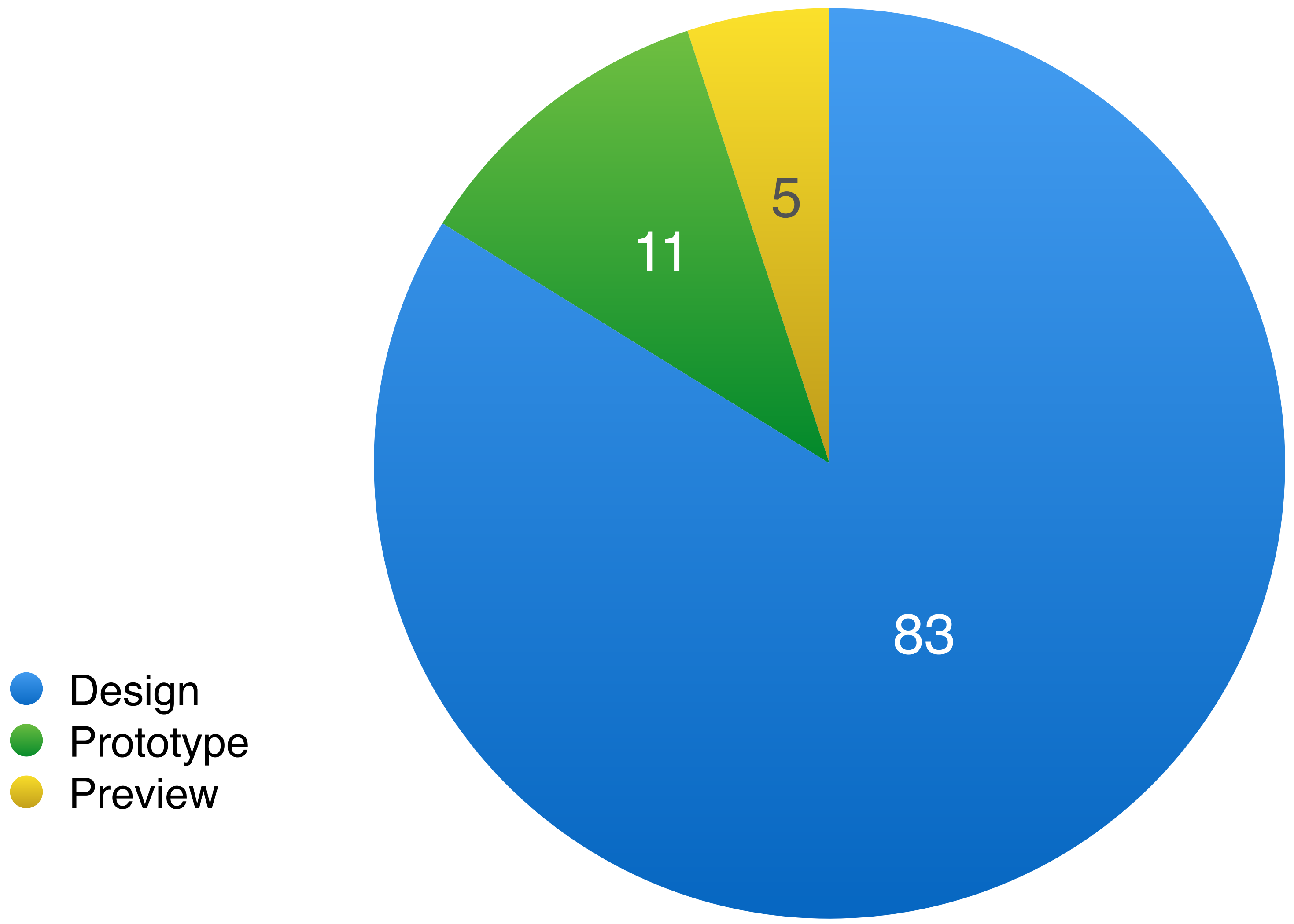
AVERAGE USAGE



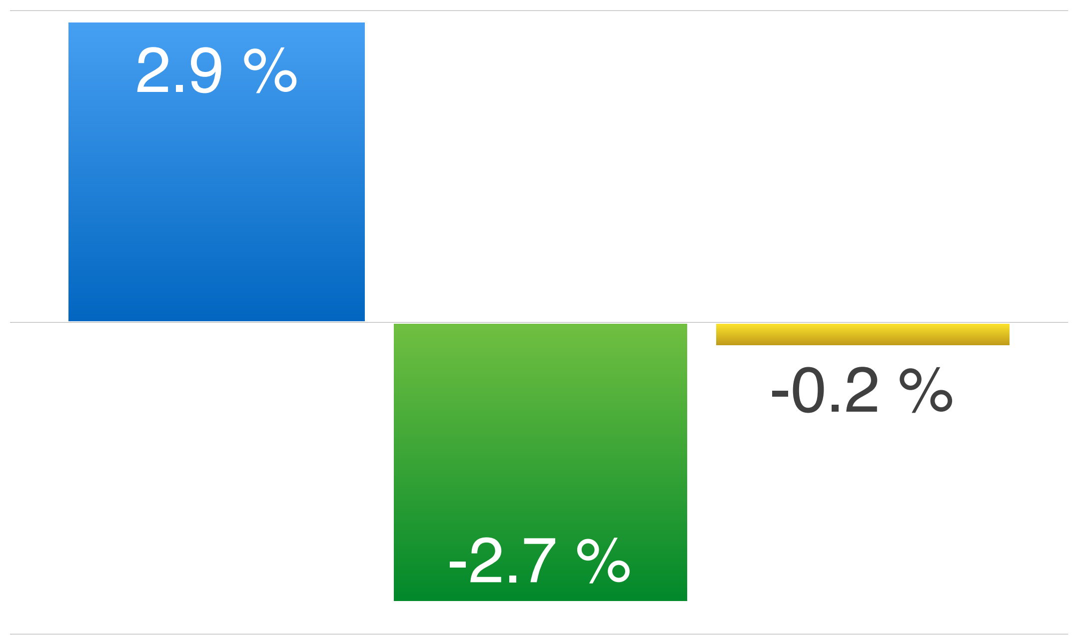
ACTION SEQUENCES



MODE PREFERENCE

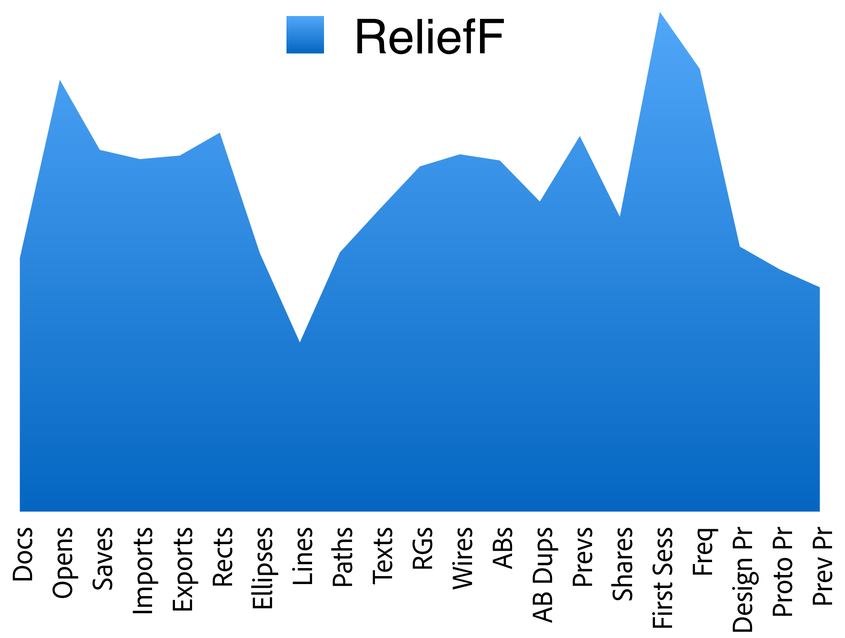


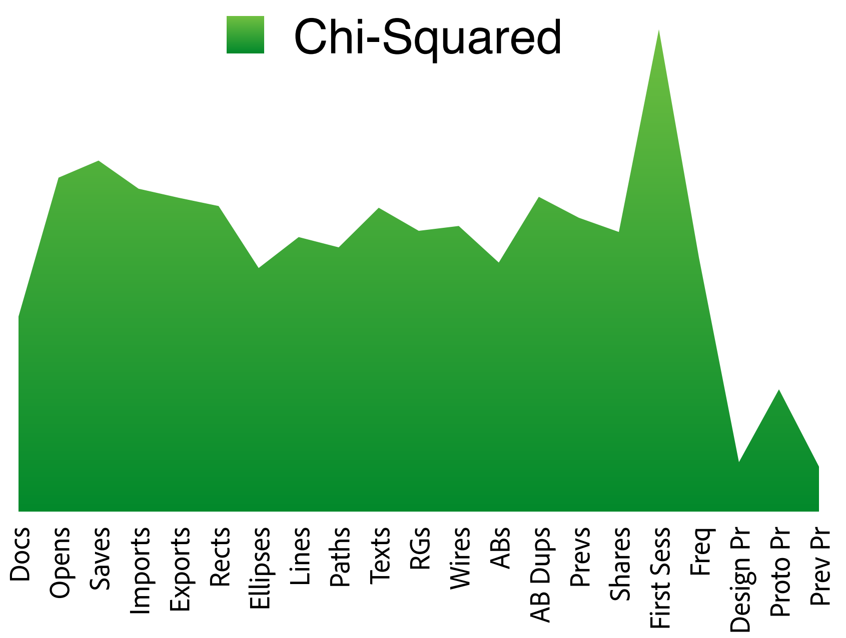
churners time spent

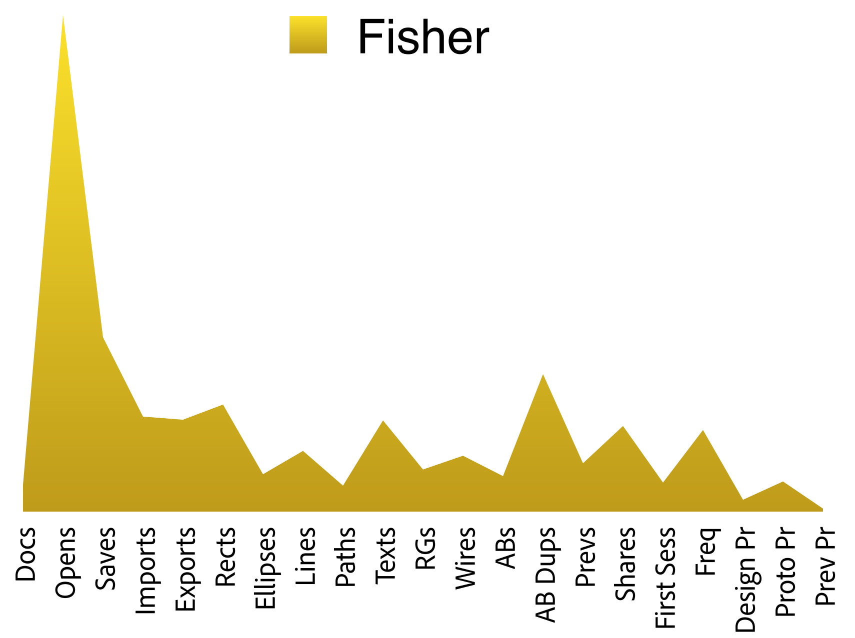


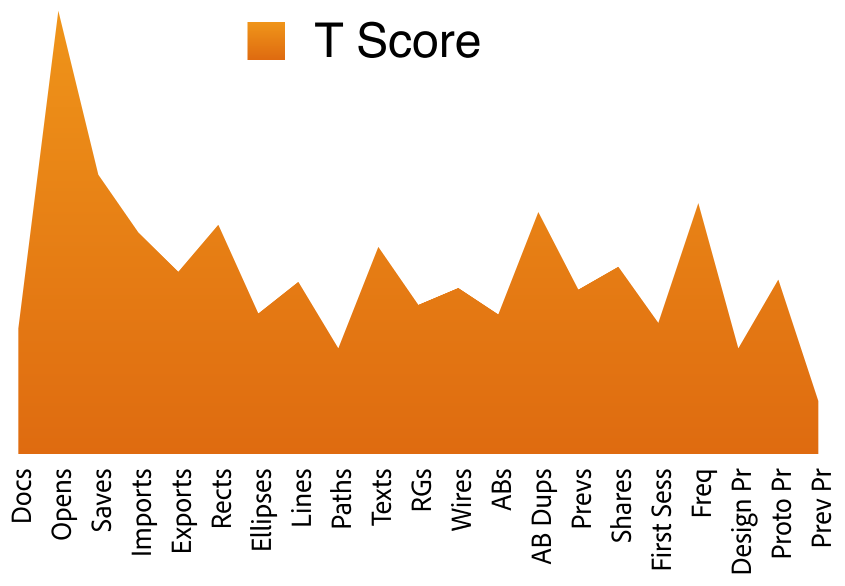
retainers difference

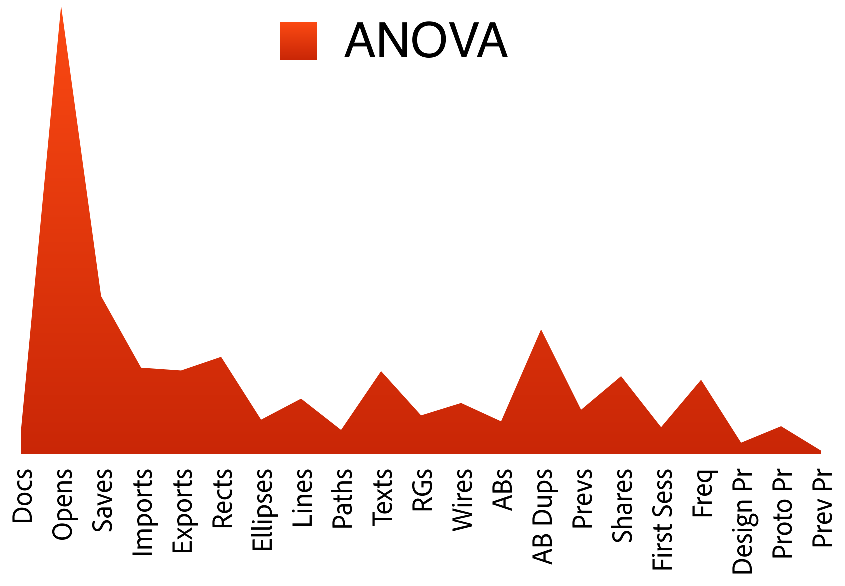
STATISTICAL SCORES

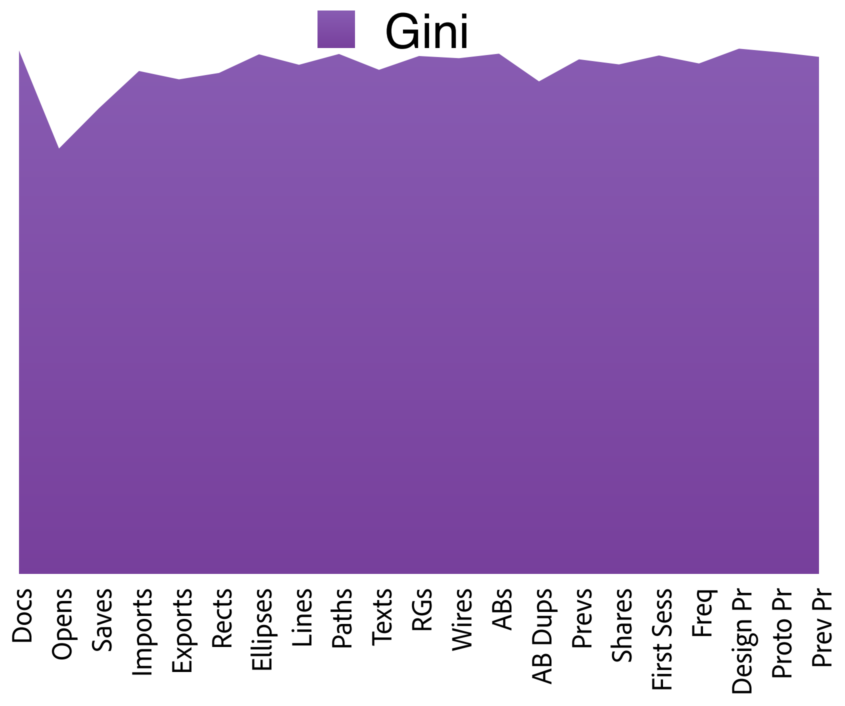




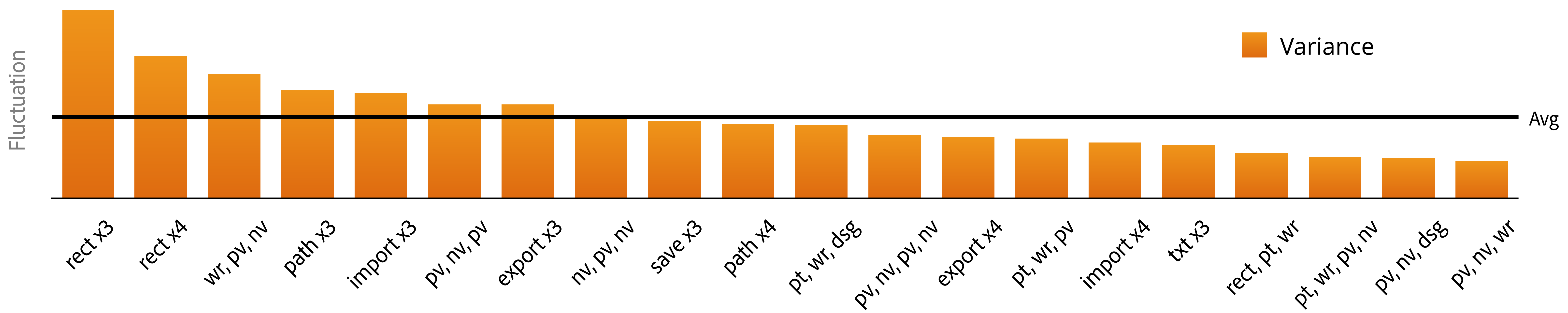


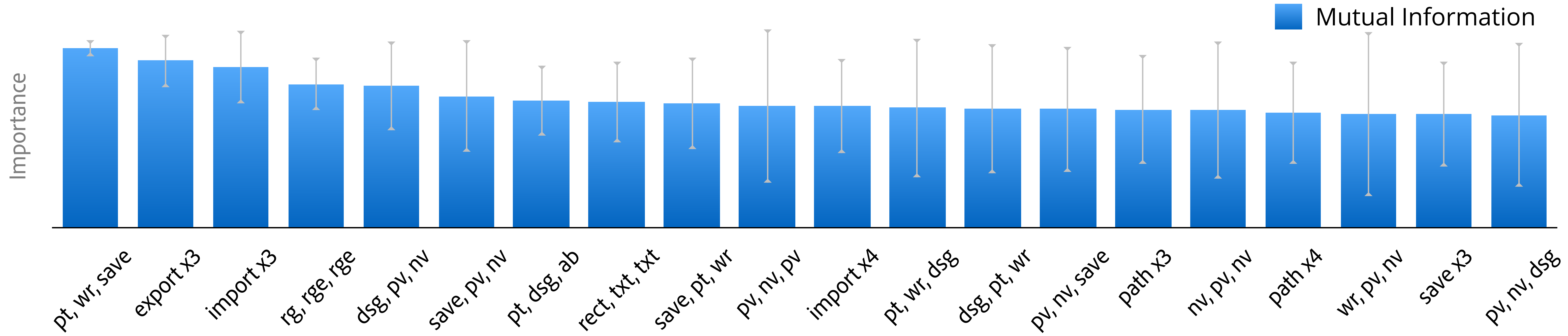






STATISTICAL METHODS





MODEL OPTIMIZATION

PIPELINE

- gives the best model for a learning task
- seeks to minimize human input
- compensates for lack of experience

MODEL OPTIMIZATION

BEFORE

1. Pick applicable learning methods on the task
   Select concrete learning **algorithms** for each method
2. Consider impactful hyper-parameters for each algorithm
   Pick sensible **ranges of values** for each hyper-parameter
3. Run **data analysis** and **statistical methods**
   Propose most impactful feature subsets
4. Decide the desired **duration** allowed for optimization

MODEL OPTIMIZATION

STEPS

1. Run exhaustive search on hyper-parameter grid on a **sample**
   Restrict hyper-parameters iterations and RFE step size based on time

2. Fit **hyper-parameters** for each model
   Using random-search (restricted)

3. Chose best **feature subset** for each model
   Try the whole dataset, proposed subsets and RFE (restricted)

4. Take best models (with diversity in mind)
   Use them as deciders for the **combining classifier**

META CLASSIFIER

classify based on the output of other algorithms,
not on examples themselves

- learn **how** to learn
- already trained many models
- learn how to best combine their decisions

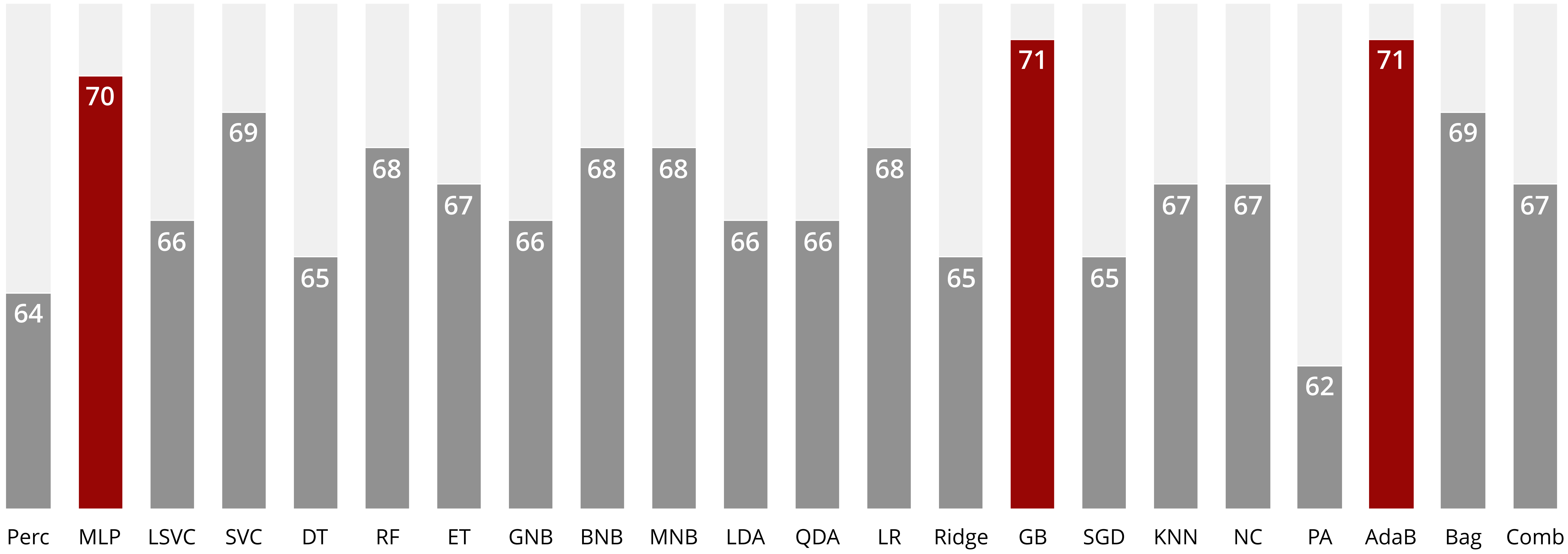
COMBINER

simple model for aggregating:
shallow NN, small RF, linear SVM

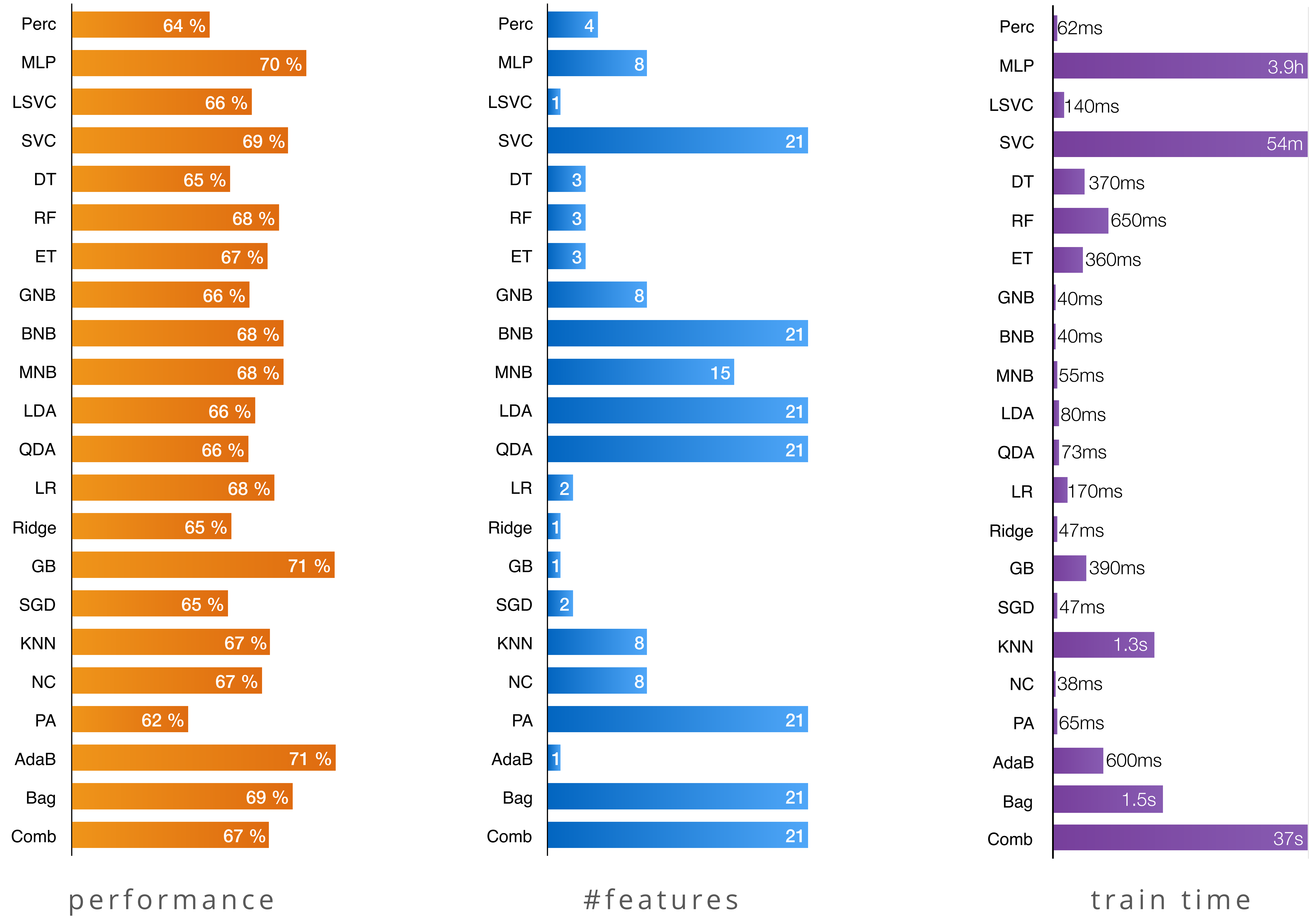
DECIDERS

take best performing models.
each has strengths and weaknesses,
compensate by promoting **diversity**

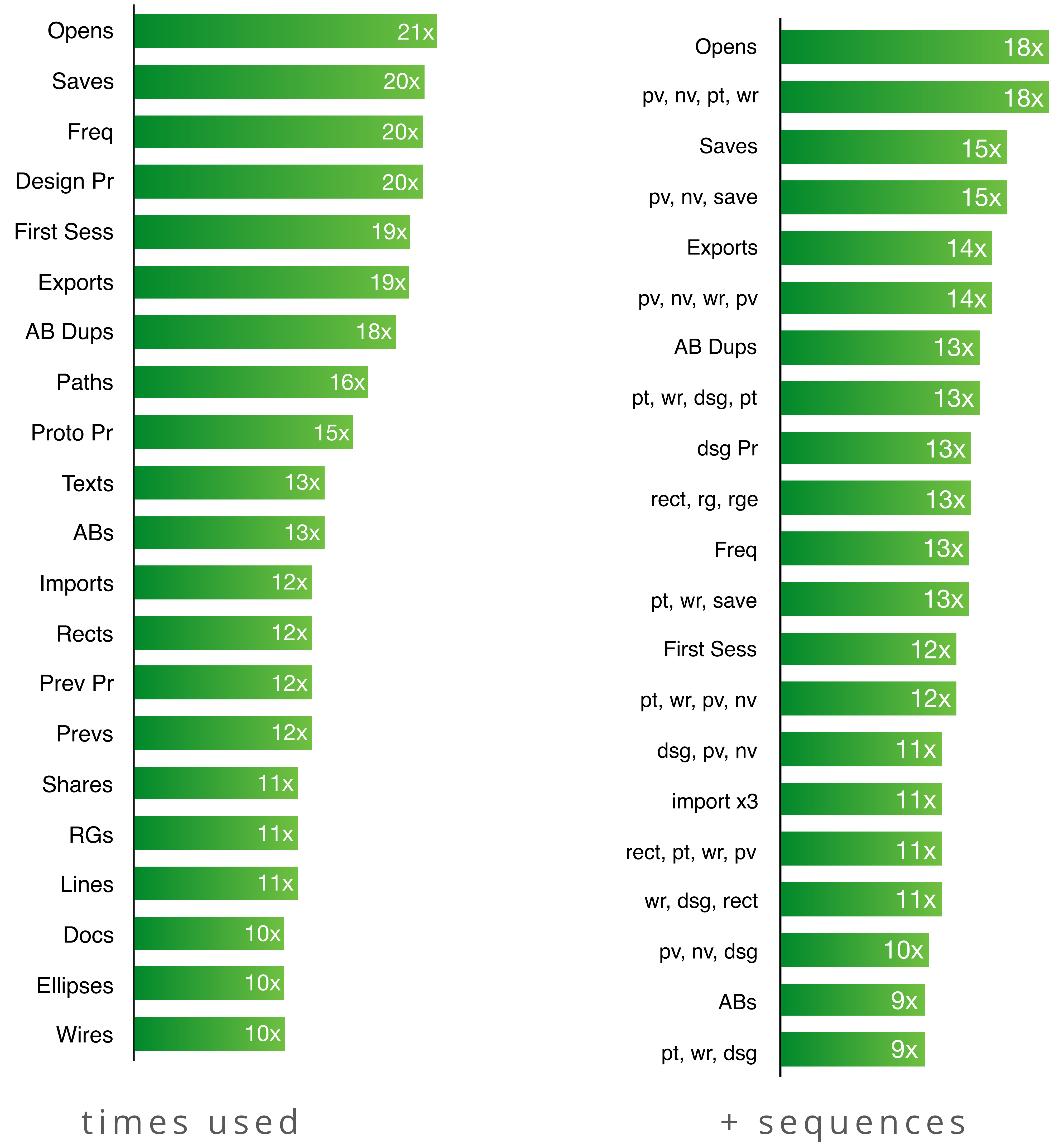
MODEL PERFORMANCE



MODEL COMPARISON



FEATURE RANKING



CONCLUSION

Important features:
- prototype, preview
- RGs, ABs

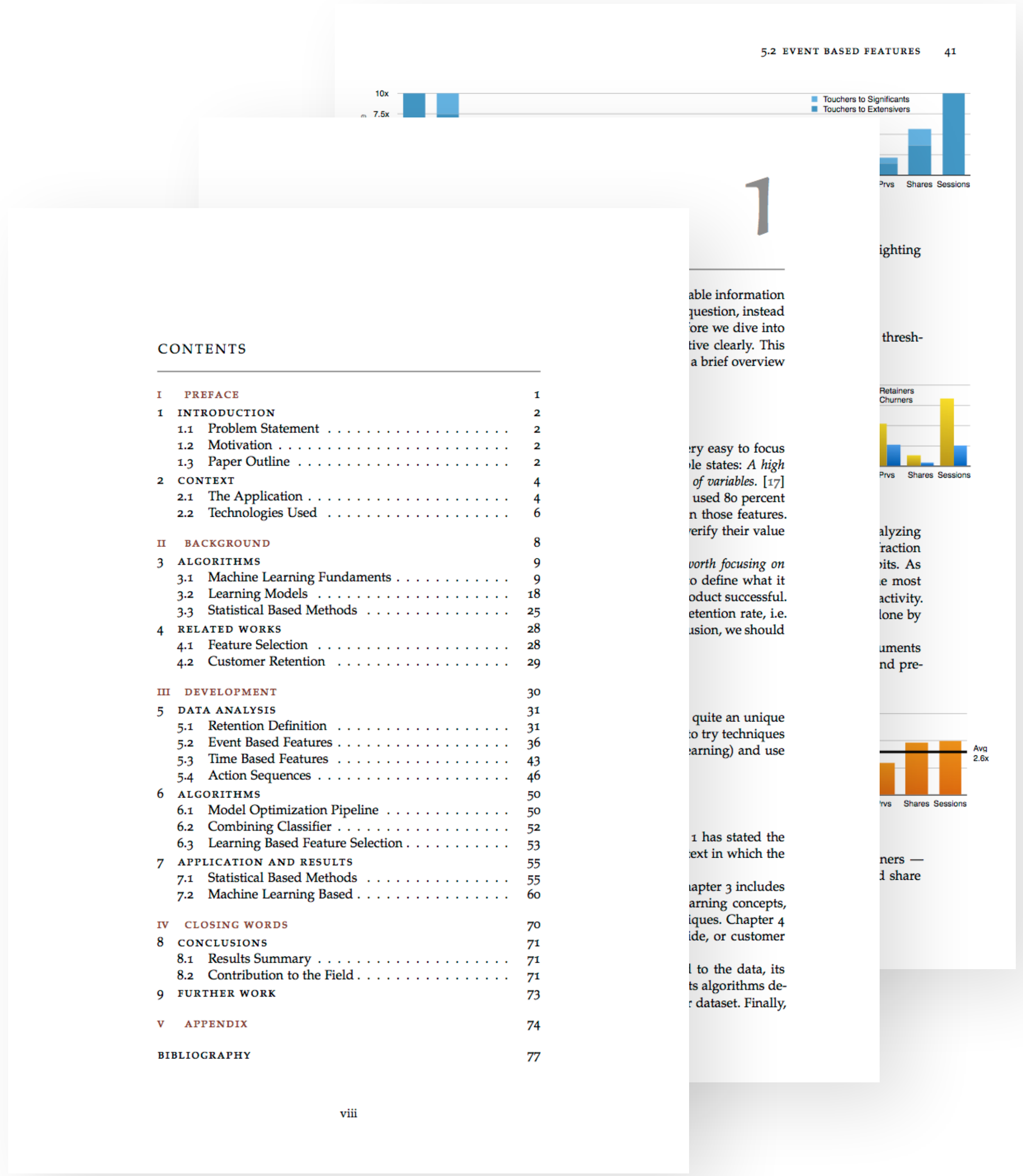
Field contribution:
- model optimization pipeline,
- combining classifier

NEXT STEPS

Technique refinement:
- continuous classification
- deep learning
- word embedding visualization

New direction:
- sequence learning
- predictive system

AVAILABLE ON REQUEST



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THESIS

87 pages

```python
from sklearn.datasets import make_hastie_10_2
from sklearn.metrics import accuracy_score


class CombiningClassifier(BaseEstimator, ClassifierMixin):
    def __init__(self, combiner=Perceptron(), deciders='default'):
        self.combiner = combiner

        if deciders == 'default':
            deciders = [SVC(), ExtraTreesClassifier(),
                        LogisticRegression(), MultinomialNB()]
        self.deciders = deciders


    def check_parameters(self):
        # Checking if the combining and deciding classifiers are
        # actually classifiers
        classifiers = [self.combiner] + self.deciders
        for clf in classifiers:
            # TODO make these exception throwers
            assert issubclass(clf.__class__, BaseEstimator)
            assert issubclass(clf.__class__, ClassifierMixin)
            # TODO use has attr fit and has attr predict
            # pass


    def combiner_input_(self, X):
        # The first row contains the predictions of the first deciding
        # classifier for every point
        # the second row has the second deciding classifier, etc
        deciders_output = [clf.predict(X) for clf in self.deciders]

        # Now on the first row there is the prediction for the first point of
        # every deciding classifier
        # on the second row the prediction for the second point etc
        return np.array(deciders_output).transpose()



    def fit(self, X, y):
        self.check_parameters()

```

CODE

3.9 kloc

ACKNOWLEDGEMENTS

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Daniel Dogaru

BIBLIOGRAPHY

C. Bishop - *Pattern Recognition and Machine Learning*
T. Hastie et al - *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*

Full list in paper

Q & A

+ feedback

THANK YOU

for your attention

ȘTEFAN NICULAE

niculae@adobe.com 10C

“An approximate answer to the right problem is worth a good deal more than an exact answer to an approximate problem”

— John Tukey, mathematician