ML for SS: Classification

Session 2

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Overview

Papers

Paper 1: Purda and Skillicorn 2015

- A fairly approachable overview of ML methods in economics
- The points the paper makes are applicable broadly in any archival/empirical discipline

Paper 2: Chahuneau et al 2012

- An application of LASSO to a context most should be familiar with: restaurant menus
- Easy to motivate LASSO in this paper – more variables than observations!

Technical Discussion: Classification

- SVM
- Tree-based algorithms

Python

- Using `sklearn` for SVM
- Using `xgboost` for XGBoost
- Using `sklearn` for hyperparameter tuning

R

- Using `caret` for SVM
- Using `xgboost` for XGBoost
- Using `tidymodels` and related packages for hyperparameter tuning

> Python is generally a bit stronger for these topics.

> There is a fully worked out solution for each language on my website, data is on eLearn.

Main application: Binary problem

- Idea: Using the same data as in Application 1, can we predict instances of intentional misreporting?
- Testing: Predicting 10-K/A irregularities using finance, textual style, and topics

Dependent Variable

Intentional misreporting as stated in 10-K/A filings

Independent Variables

- 17 Financial measures
- 20 Style characteristics
- 31 10-K discussion topics

This test mirrors a subset of Brown, Crowley and Elliott (2020 JAR)

Same problem and data as last week's binary problem

Main application: A Linear problem

- Idea: Discussion of risks, such as as foreign currency risks, operating risks, or legal risks should provide insight on the volatility of future outcomes for the firm.
- Testing: Predicting future stock return volatility based on 10-K filing discussion

Dependent Variable

- Future stock return volatility

Independent Variables

- A set of 31 measures of what was discussed in a firm's annual report

> This test mirrors Bao and Datta (2014 MS)

> Same problem and data as last week's linear problem

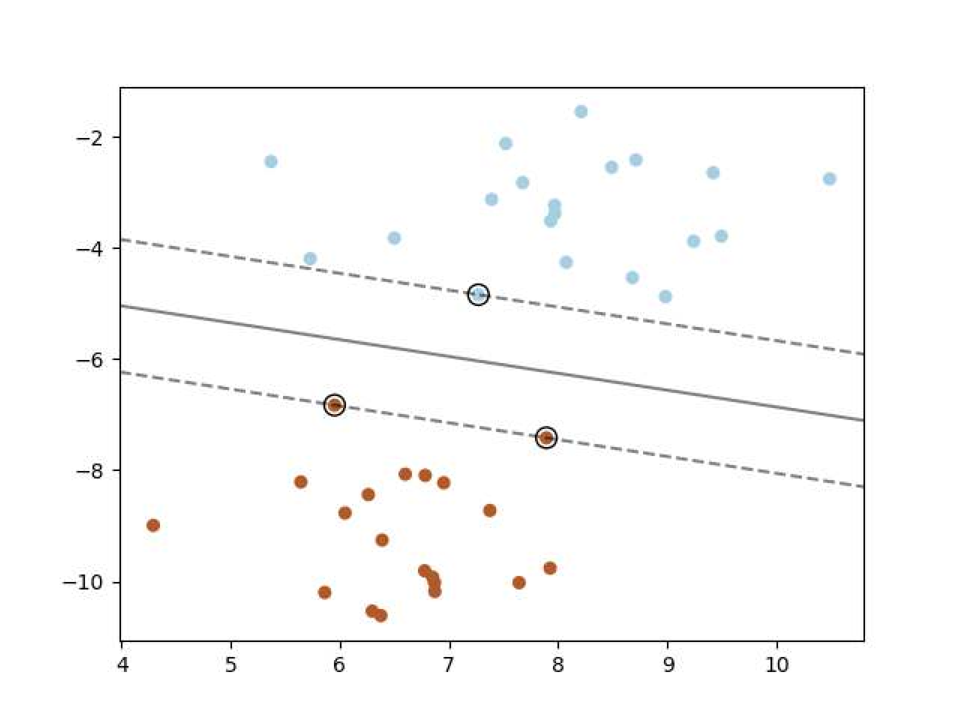
SVM: Support Vector Machine

What is SVM?

Simpler case: Binary Classification

- SVM-type algorithms generally focus on separability under some tolerance for error
  - This is quite different from our regression approaches
    - Regression focuses on *minimizing an error function*

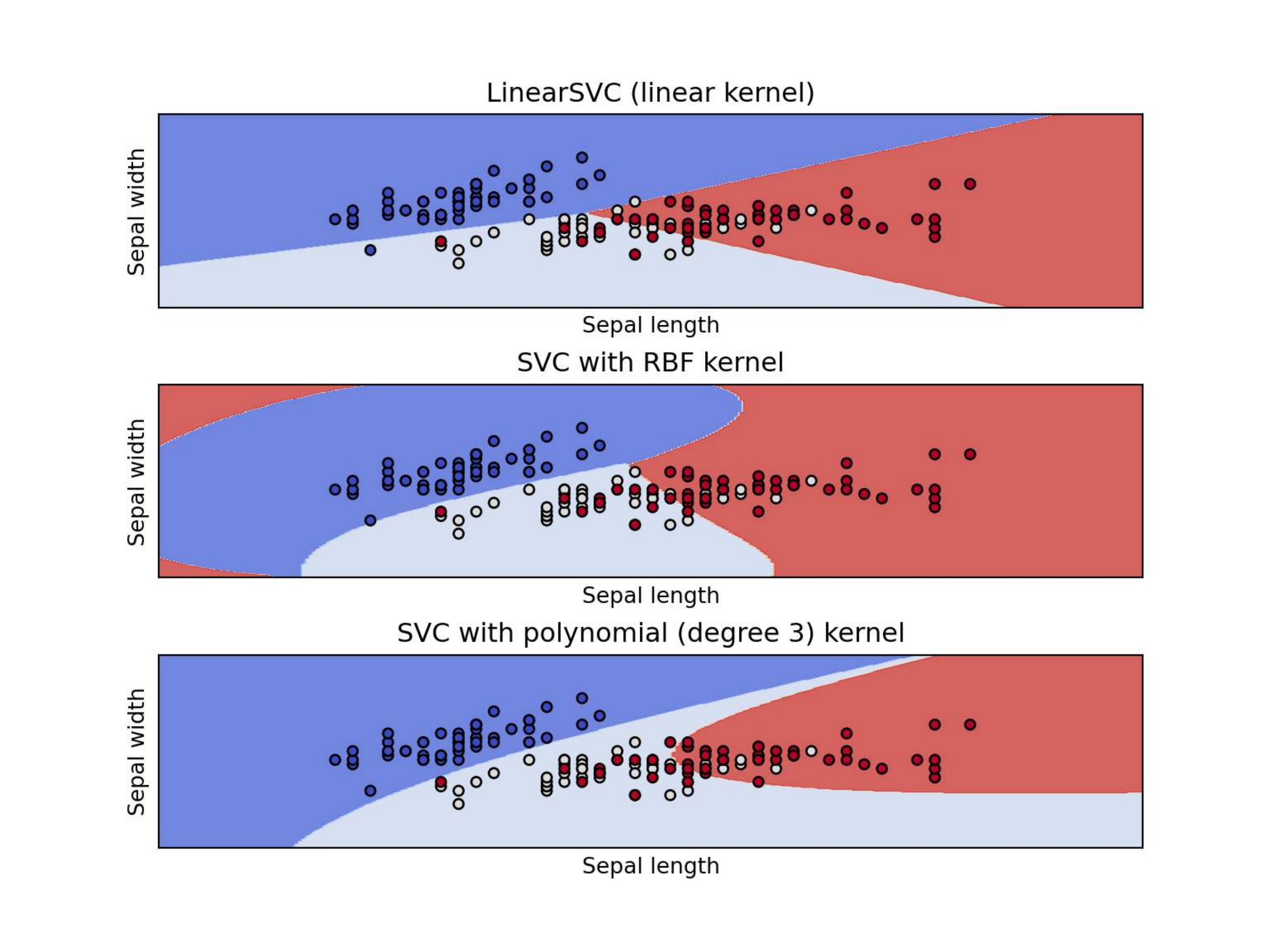
- Note how in this example the points that matter are those that are on the error boundaries
- The rest of the points aren't affecting the outcome much
  - You could shift them around on their respective side of the line with minimal impact



From the sklearn documentation

What are the benefits of SVM?

1. Non-linear kernels
   - SVM can be linear or non-linear
     - 3 examples to the right, adapted from the sklearn documentation
2. Different objective function than regression
   - Fits better with classification, conceptually
3. Can work with non-numeric data (text, images, graphs)



What are the costs of SVM?

1. Doesn't work well on noisy data
2. Can be slow to train on datasets with many observations
   - More than 10,000 observations leads to a lot of slow down for non-linear kernels
3. Difficult to interpret model when using a non-linear kernel
4. Can be difficult to pick an optimal kernel

Implementing SVM in python

- For this we will use `sklearn` again
- To keep things simple and interpretable, we will use linear kernels in these examples

Binary classification

- Fast linear model:
  - `sklearn.svm.LinearSVC()`
- General model:
  - `sklearn.svm.SVC()`

Regression

- Fast linear model:
  - `sklearn.svm.LinearSVR()`
- General model:
  - `sklearn.svm.SVR()`

- Both linear methods have a hyperparameter `C` which controls the amount of regularization (inversely)
  - We can tune this using `sklearn` as well!

Why are there two ways each to run a linear SVM model?

- The two ways use different backends
  - The `LinearSV_` methods use a backend called `liblinear`
  - The `SV_` methods use a backend called `libsvm`
- `liblinear` is faster but only supports linear kernels
  - Time to run is roughly linear in the number of observations
  - `libsvm` is fast on small samples, but time increase for additional observations is polynomial
- The results aren't quite the same across backends
  - `liblinear` uses a penalized intercept while `libsvm` does not
  - `liblinear` optimizes a "squared hinge" loss function while `libsvm` optimizes "hinge" loss

$$hinge(x,y) = \max(0, 1 - y \cdot f(x)), \quad y \in \{-1,+1\}, \quad f(x) \in \mathbb{R}$$

> Both developed out of National Taiwan University, and both maintained by the same professor

Implementing LinearSVC for irregularity detection

- To train a simple linear SVM classifier, we can call `svm.LinearSVC()` pretty much the same way that we used `linear_model.Lasso()` earlier
  - Note: The `dual=False` option is to maintain efficiency when the number of observations is great than the number of variables

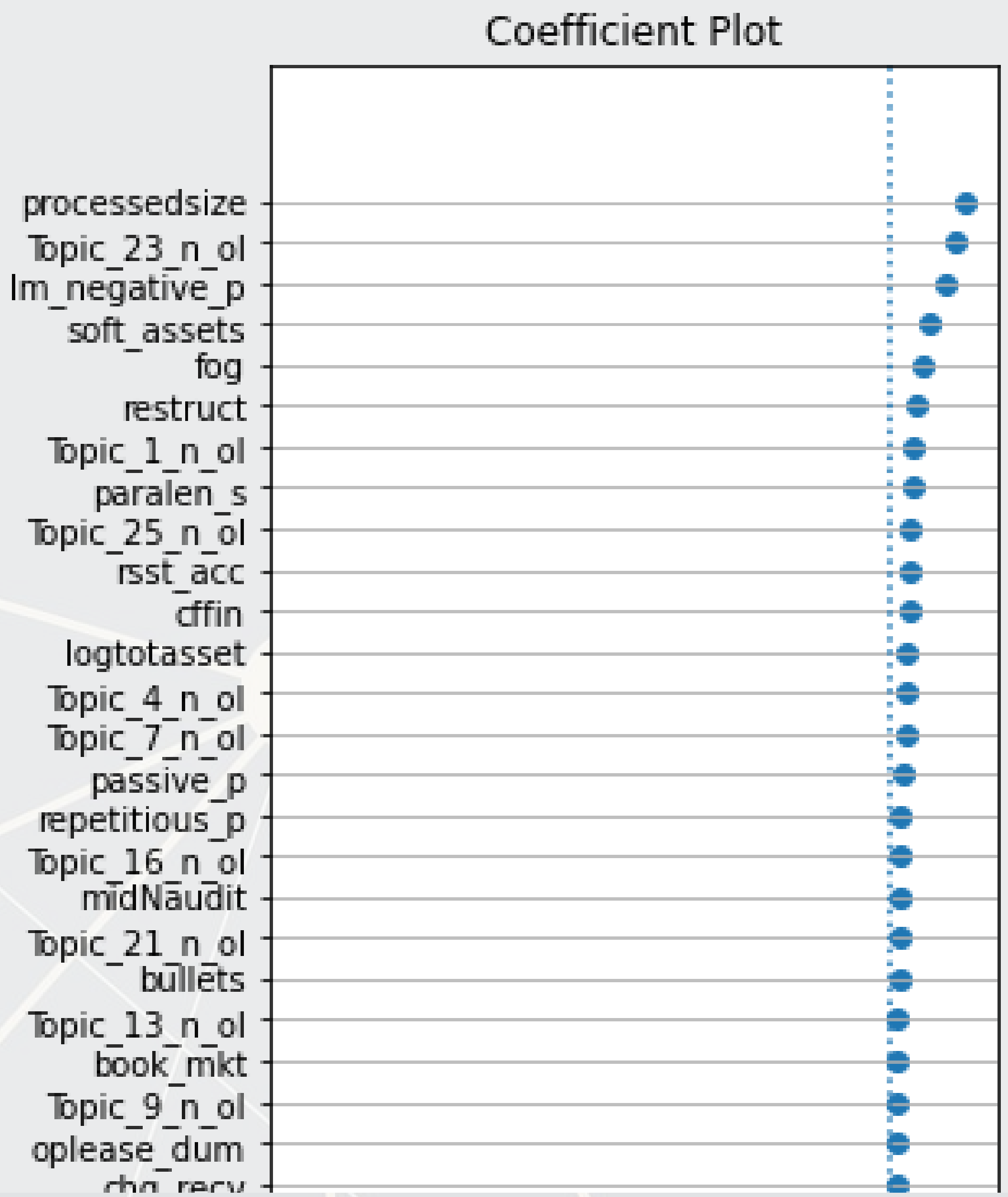
```python
model_svc = svm.LinearSVC(C=1, dual=False)
model_svc.fit(train_X_logistic, train_Y_logistic)
```

- No regression table built in, but we can visualize it with `coefplot()`

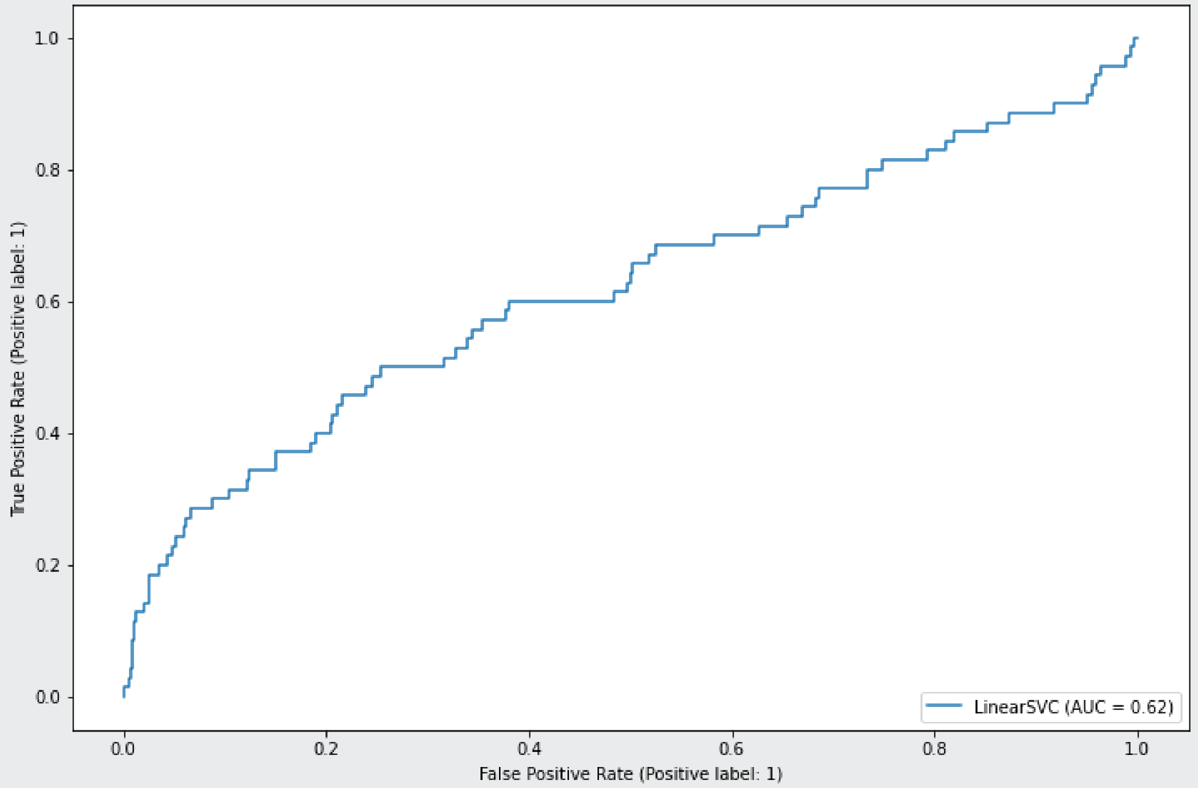
```python
coefplot(vars_logistic, model_svc.coef_)
```

Visualizing LinearSVC for irregularity detection

```python
coefplot(vars_logistic, model_svc.coef_)
```




```python
metrics.plot_roc_curve(model_svc, test_X_logistic,
                       test_Y_logistic)
```



Optimizing the C parameter

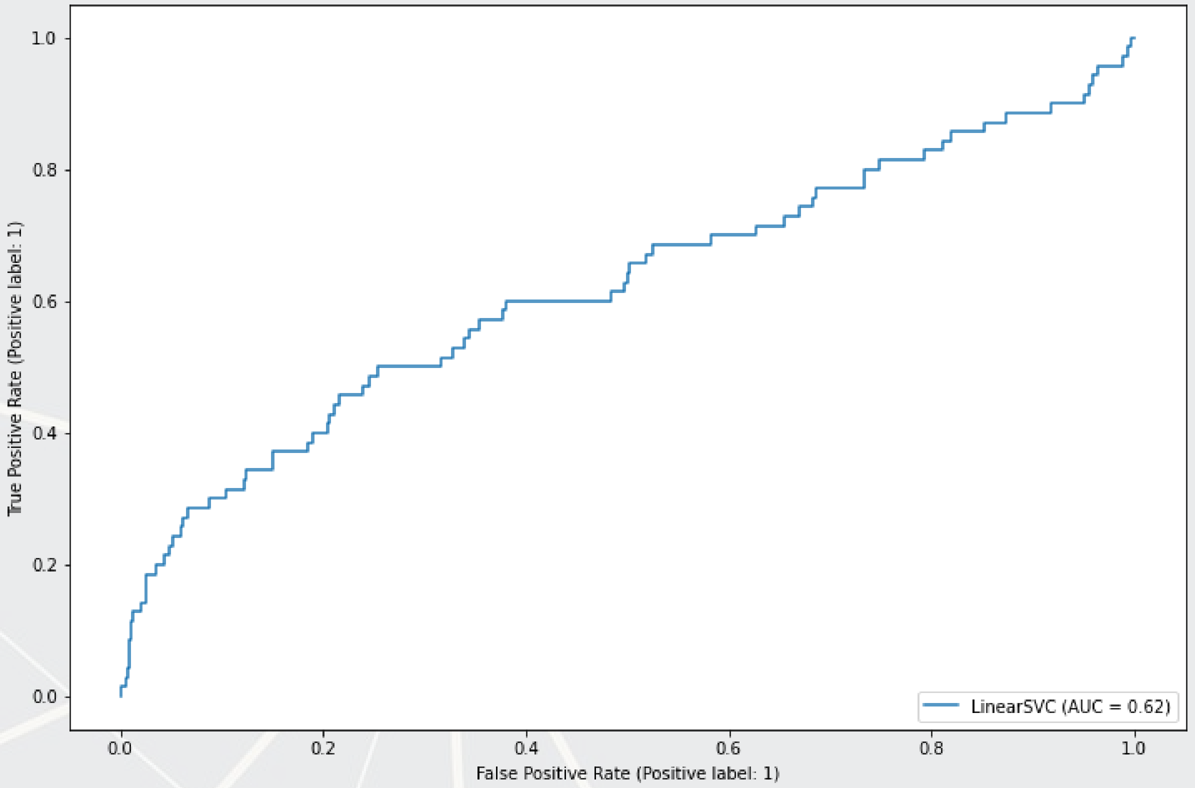
```python
C_range = np.logspace(-2, 6, 9)
param_grid = dict(C=C_range)
cv = model_selection.StratifiedShuffleSplit(n_splits=5, test_size=0.2, random_state=1)
grid_svc = model_selection.GridSearchCV(svm.LinearSVC(dual=False), param_grid=param_grid, cv=cv)
grid_svc.fit(train_X_logistic, train_Y_logistic)
print("The best parameter is C=%s with a score of %0.2f"
      % (grid_svc.best_params_['C'], grid_svc.best_score_))
```

```
## [1] "The best parameter is C=0.01 with a score of 0.99"
```

Comparison pre- vs post-optimization: ROC

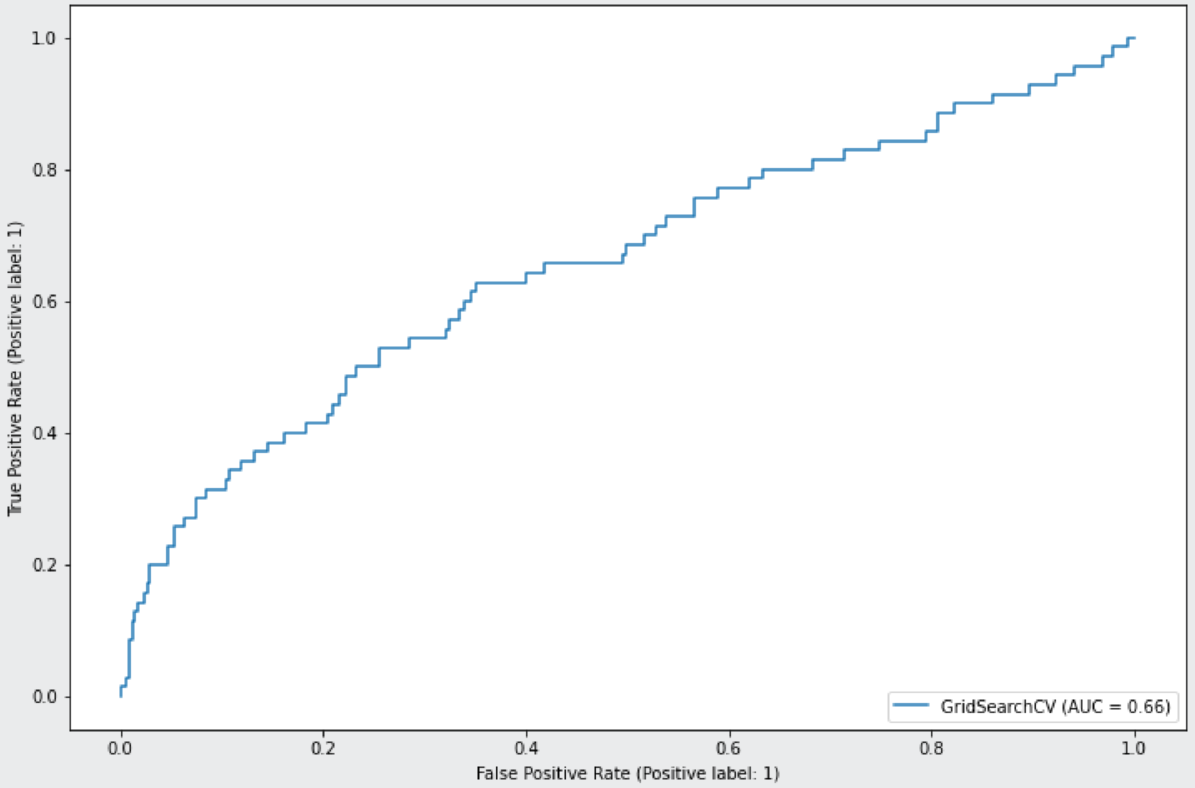
Unoptimized

```python
metrics.plot_roc_curve(model_svc, test_X_logistic,
                       test_Y_logistic)
```



Optimized

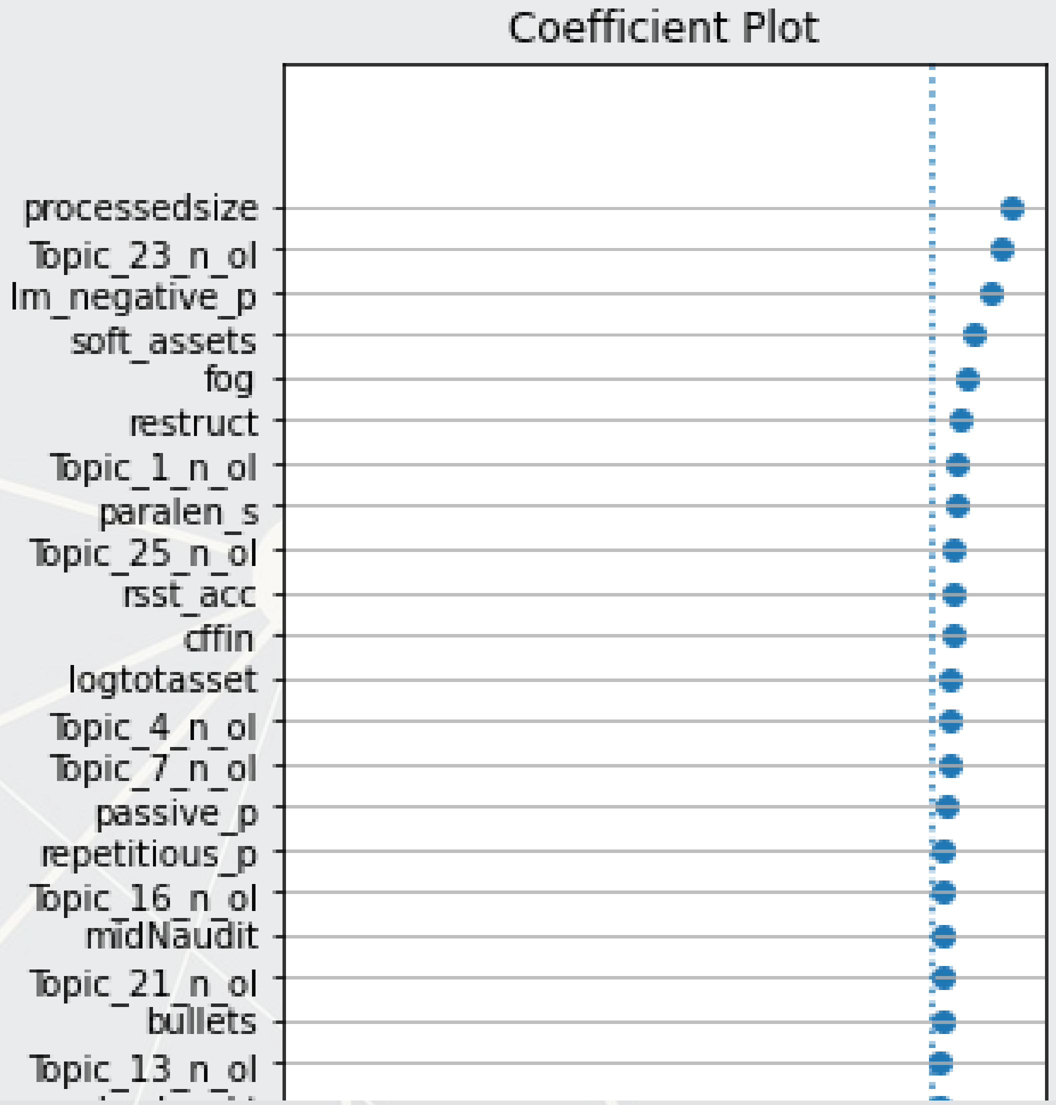
```python
metrics.plot_roc_curve(grid_svc, test_X_logistic,
                       test_Y_logistic)
```



Comparison pre- vs post-optimization: Coefficients

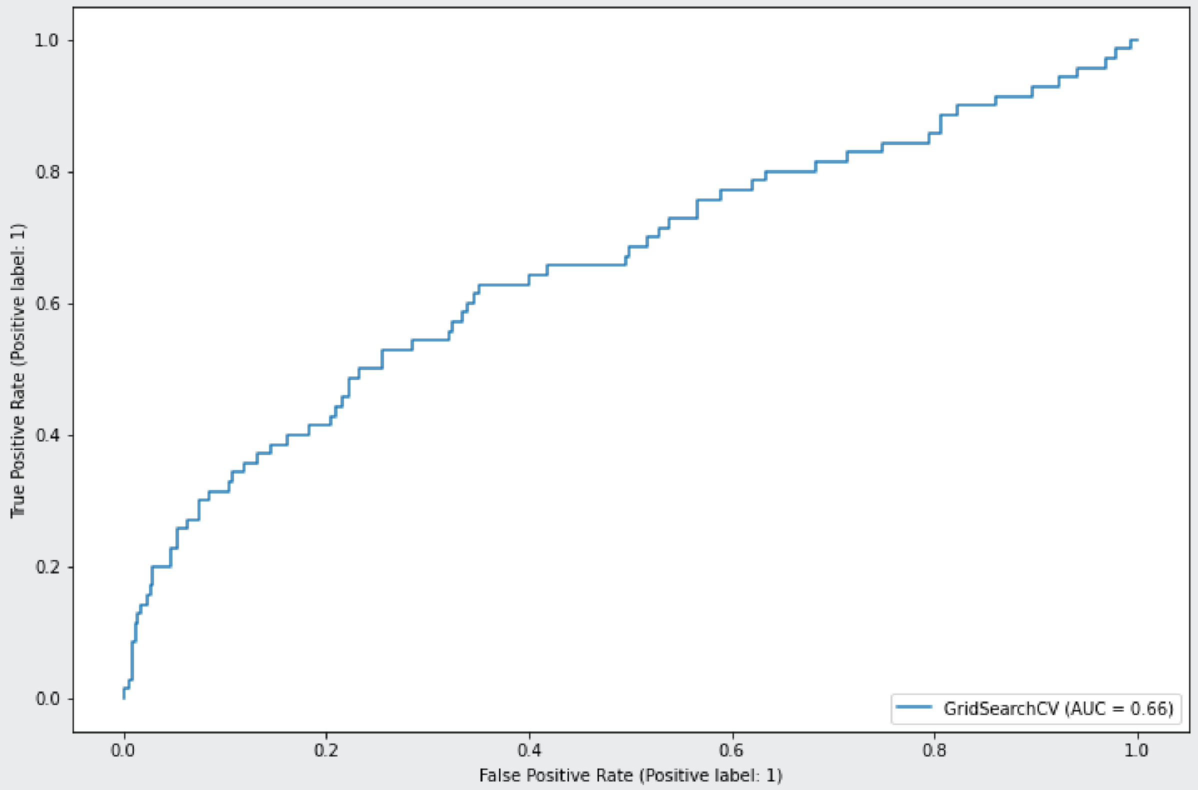
Unoptimized

```python
coefplot(vars_logistic, model_svc.coef_)
```



Optimized

```python
coefplot(vars_logistic,
  grid_svc.best_estimator_.coef_)
```



Visualizing with UMAP

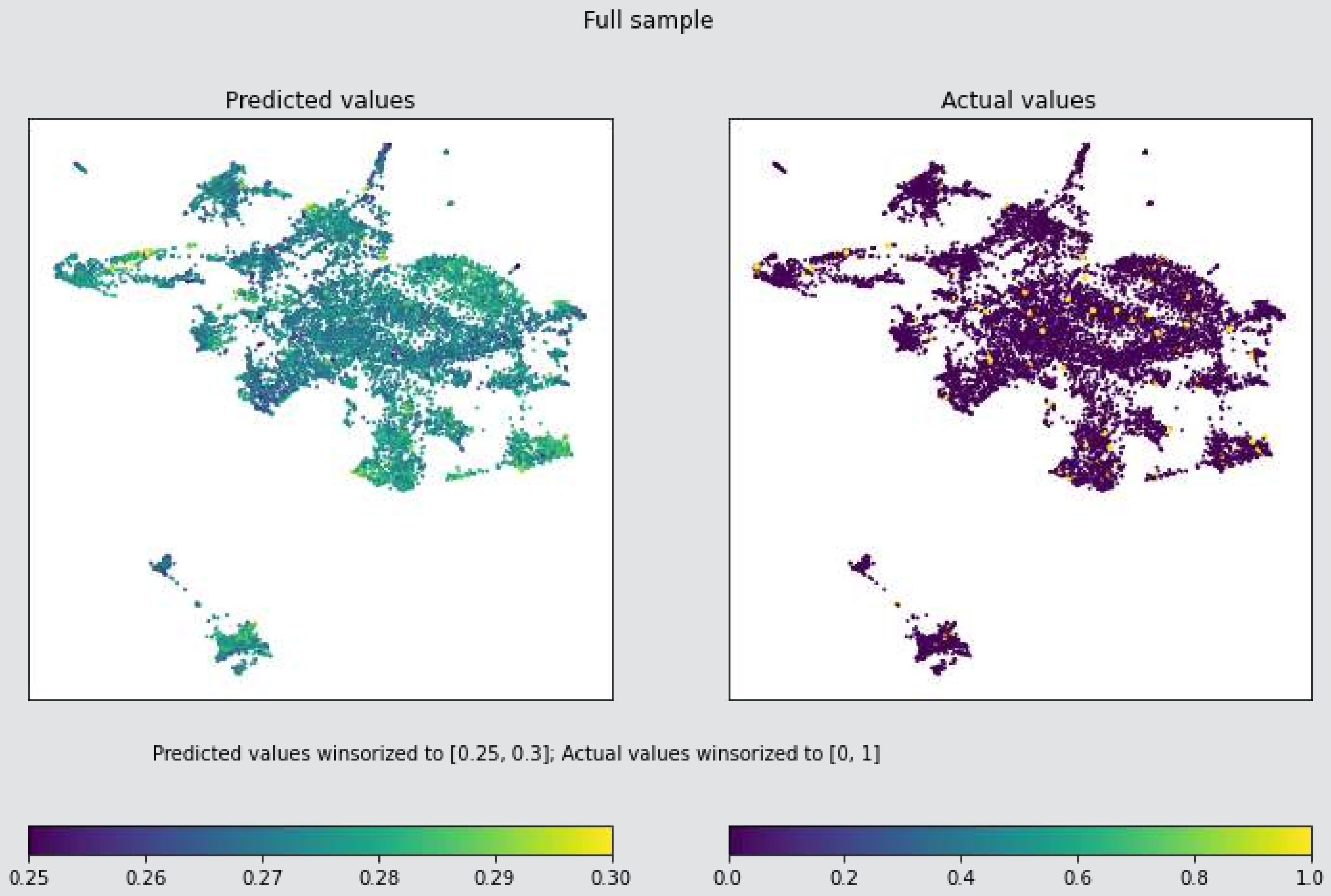
> What is UMAP?

- UMAP stands for Uniform Manifold Approximation and Projection for Dimension Reduction
  - From Leland, Healy and Melville (2018) (2k+ cites already)
- It is useful for dimensionality reduction, like PCA
  - We will use it to reduce 68 dimensions down to 2
- It is useful for plotting 2 dimensional representations of high dimensional data by maintaining local distance structures, like t-SNE
  - Unlike t-SNE, it is efficient to run

> UMAP essentially uses Reimannian manifolds and tries to maintain geodesic distance around a point – it is well supported theoretically

Visualizing what SVM is doing using UMAP

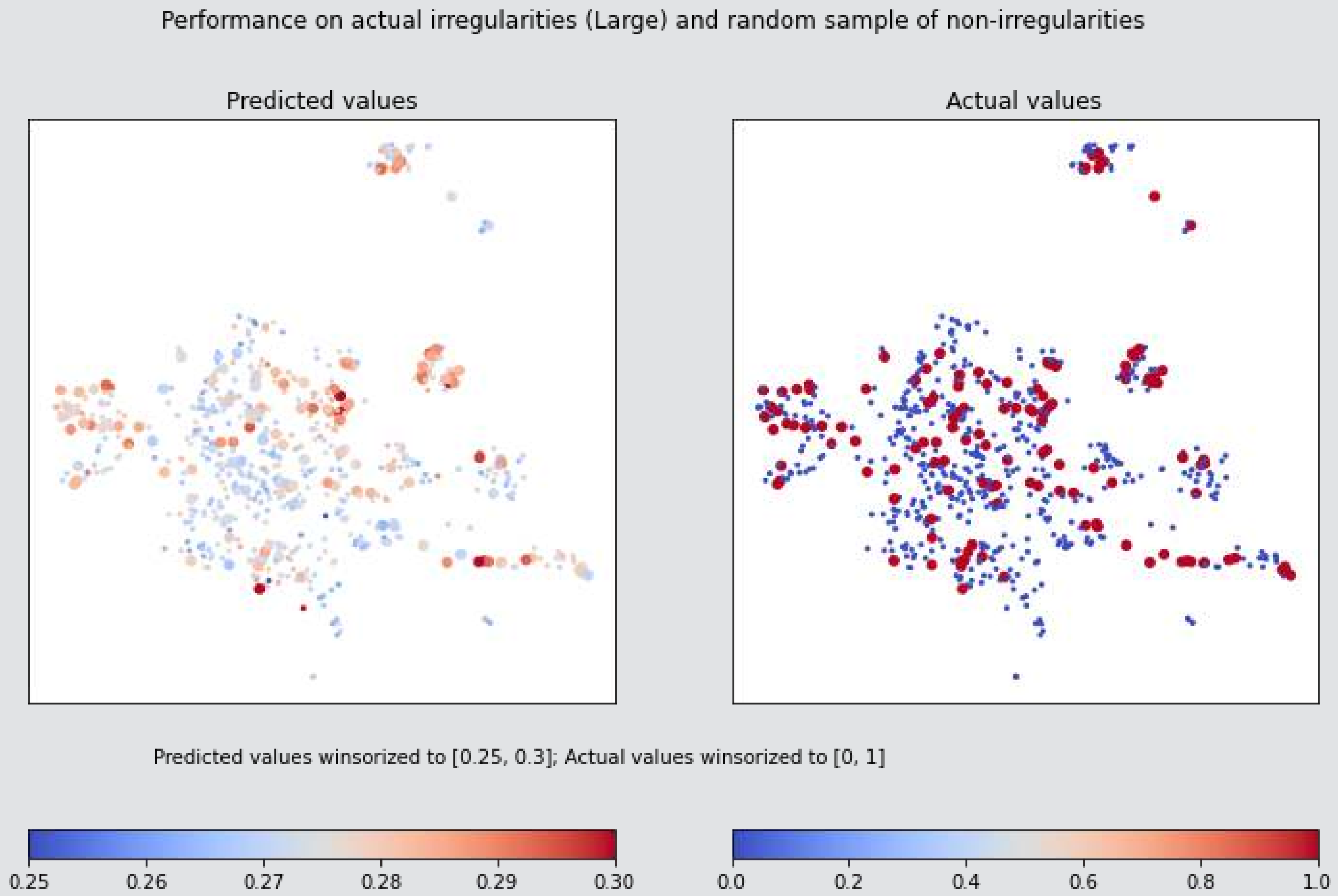
```python
train_Yhat_logistic = logistic(grid_svc.decision_function(train_X_logistic))
umap_compare_svm(train_X_logistic, train_Yhat_logistic, train_Y_logistic,
                 clip=[[0.25, 0.3], [0, 1]], binary=5, title="Full sample")
```



The data is really noisy

Visualizing what SVM is doing using UMAP

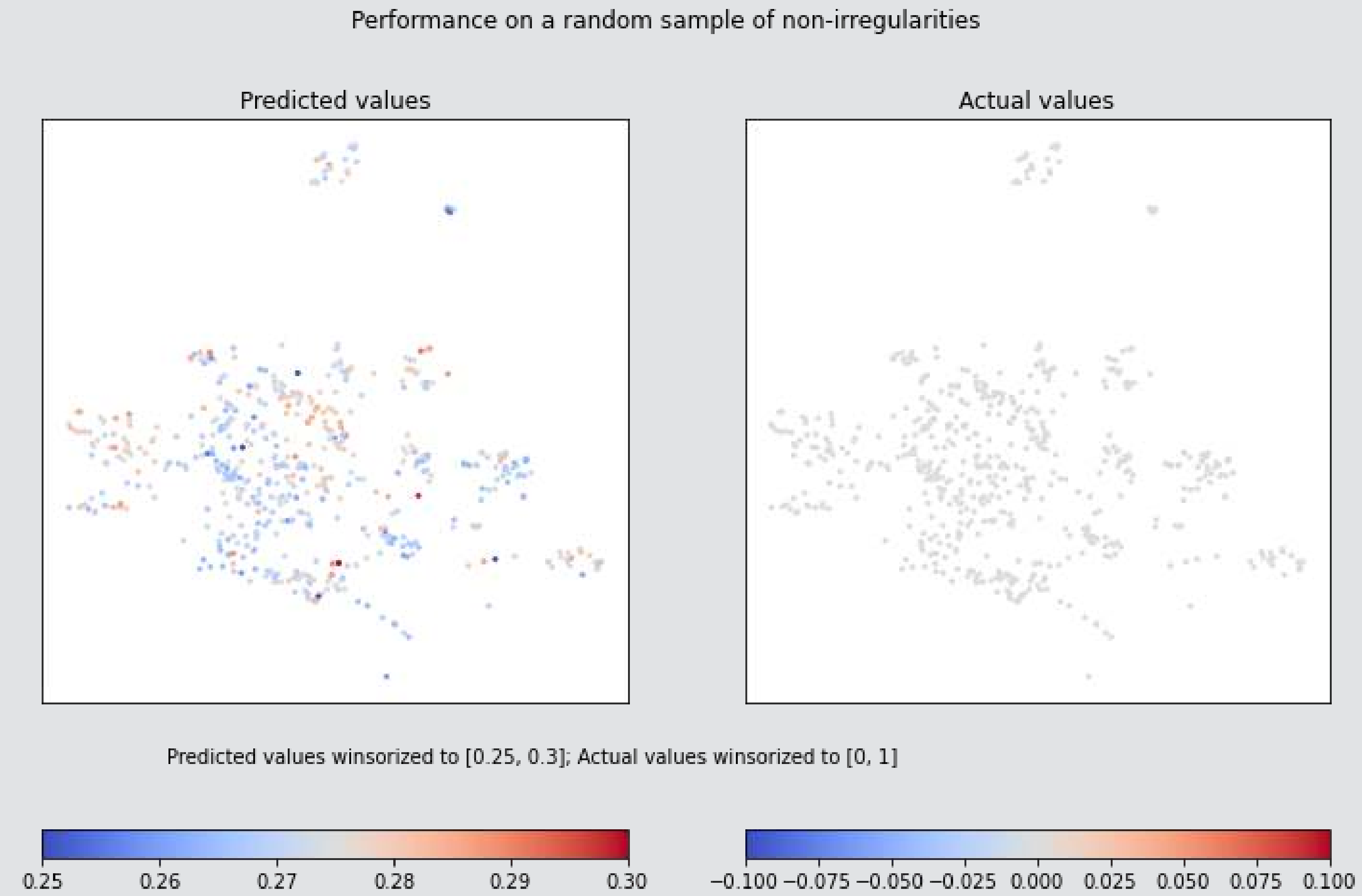
```
umap_compare_svm(train_X_logistic, train_Yhat_logistic, train_Y_logistic, clip=[[0.25, 0.3], [0, 1]], cmap='coolwarm', binary=
                 subset=((train_Y_logistic==1) | (np.random.rand(len(train_Y_logistic))<0.05)),
                 title="Performance on actual irregularities (Large) and random sample of non-irregularities")
```



Type I errors are pretty minimal – the algorithm is rarely very off

Visualizing what SVM is doing using UMAP

```
umap_compare_svm(train_X_logistic, train_Yhat_logistic, train_Y_logistic, clip=[[0.25, 0.3], [0, 1]], cmap='coolwarm', binary=
                 subset=((train_Y_logistic==0) & (np.random.rand(len(train_Y_logistic))<0.05)),
                 title="Performance on a random sample of non-irregularities")
```



> There are definitely some combinations of parameters that are consistently leading to Type II errors

SVM for regression: SVR

```python
model_svr = svm.LinearSVR(C=1, dual=False,
  loss='squared_epsilon_insensitive')
model_svr.fit(train_X_linear, np.ravel(train_Y_linear))
```

```python
C_range = np.logspace(-4, 6, 11)
param_grid = dict(C=C_range)
cv = model_selection.KFold(n_splits=5)
grid_svr = model_selection.GridSearchCV(
  svm.LinearSVR(dual=False,
  loss="squared_epsilon_insensitive"),
  param_grid=param_grid, cv=cv)
grid_svr.fit(train_X_linear, np.ravel(train_Y_linear))
print("The best parameter is C=%s with a score of %0.2f"
      % (grid_svr.best_params_['C'], grid_svr.best_score_
```

```
## [1] "The best parameter is C=0.0001 with a score of 0.
```

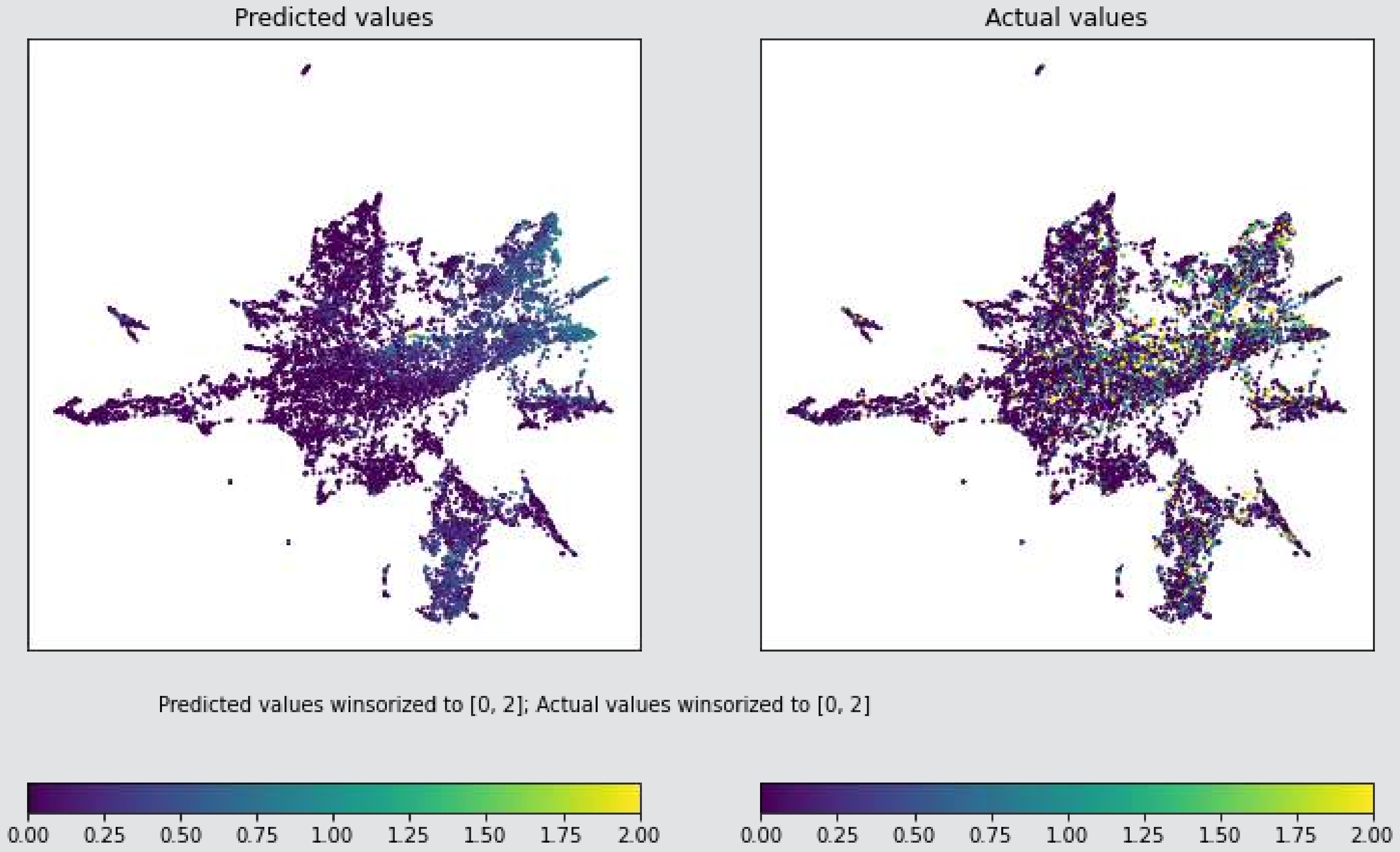
SVR coefficients

```python
coefplot(vars_linear, model_svr.coef_)
```

```python
coefplot(vars_linear, grid_svr.best_estimator_.coef_)
```

Visualizing SVR with UMAP

```python
train_Yhat_linear = model_svr.predict(train_X_linear)
umap_compare_svm(train_X_linear, train_Yhat_linear, train_Y_linear, clip=[[0, 2], [0, 2]])
```



> Here we see some clusters that are indeed higher in volatility being picked up correctly by SVM

Using R for the above

- We can use `tidymodels` to handle training of the model
  - It will offload the model computation to `kernlab`
- `tidymodels` is a collection of packages intended to serve as a spiritual successor to `caret`
- It is a collection of packages aimed at making ML workflows easier in R, much like what Scikit-learn does for python
  - `parsnip`, `recipes`, `rsample`, `dials`, `yardstick`, etc.
- It is still rough around the edges, but it is fairly functional

Step 1: Make a recipe for your data

- *Recipes* serve as a guide on how to preprocess your data
  - There are many possible steps
- This keeps preprocessing quick and transparent

```r
recipe_svm <-
  recipe(BCE_eq, data = train)  %>%
  step_zv(all_predictors()) %>% # remove any zero variance predictors
  step_center(all_predictors()) %>%   # Center all prediction variables
  step_scale(all_predictors()) %>%  # Scale all prediction variables
  step_intercept() %>% # Add an intercept to the model
  step_num2factor(all_outcomes(), ordered = T, levels=c("0","1"),
                  transform = function(x) x + 1, skip = TRUE)   # Convert DV to factor
```

Step 2: Define your ML model

- There are many built-in models in `tidymodels`
- For SVM, we will use `svm_linear`
  - Note how we specify `tune()` to the `cost` parameter
    - This is how we tell it where the grid search will go later!
- Setting mode to classification ensures we use something like SVC rather than SVR
- We can change the backend package by setting a different engine, with minimal changes needed to the rest of our code!

```r
model_svm <-
  svm_linear(cost = tune()) %>%
  set_mode("classification") %>%
  set_engine("kernlab")
```

Step 3: Define a workflow

- Workflows piece together the larger elements of a tidy model
- Simplifies some of the hassle of using functions across `tidymodels` packages

```r
workflow_svm <- workflow() %>%
  add_model(model_svm) %>%
  add_recipe(recipe_svm)
```

Step 4: Tie up loose ends

- We need to set a cross validation: `vfold_cv()`
- We need to specify the metric to track: `metric_set()`
- We need to set our grid search's grid: `expand_grid()`

```r
folds_svm <- vfold_cv(train, v=10)  # from rsample
metrics_svm = metric_set(roc_auc)  # from yardstick
grid_svm <- expand_grid(cost = exp(seq(-10,0, length.out=10)))
```

Step 5: Run the model

> We have everything we need to run the model

```r
svm_fit_tuned <- tune_grid(workflow_svm,
                           grid = grid_svm,
                           resamples = folds_svm,
                           metrics=metrics_svm)
```

- `tune_grid()` will execute the workflow:
  1. Standardize our training data
  2. Run the model
  3. Apply 10-fold CV to it
  4. Track ROC AUC for each model run
- The resulting fitted model can then be analyzed

See which model was the best

```r
show_best(svm_fit_tuned, metric = "roc_auc")
```

```
##           cost .metric .estimator      mean  n    std_err               .config
## 1 4.189421e-04 roc_auc     binary 0.6369609 10 0.02587312 Preprocessor1_Model03
## 2 1.379128e-04 roc_auc     binary 0.6157198 10 0.02662090 Preprocessor1_Model02
## 3 4.539993e-05 roc_auc     binary 0.6060063 10 0.03195342 Preprocessor1_Model01
## 4 3.865920e-03 roc_auc     binary 0.6053433 10 0.02400210 Preprocessor1_Model05
## 5 1.174363e-02 roc_auc     binary 0.5987661 10 0.02568714 Preprocessor1_Model06
```

Step 6: Re-run the model with the full data

```r
svm_final <- workflow_svm %>%
  finalize_workflow(
  select_best(svm_fit_tuned, "roc_auc")
) %>%
  fit(train)
```

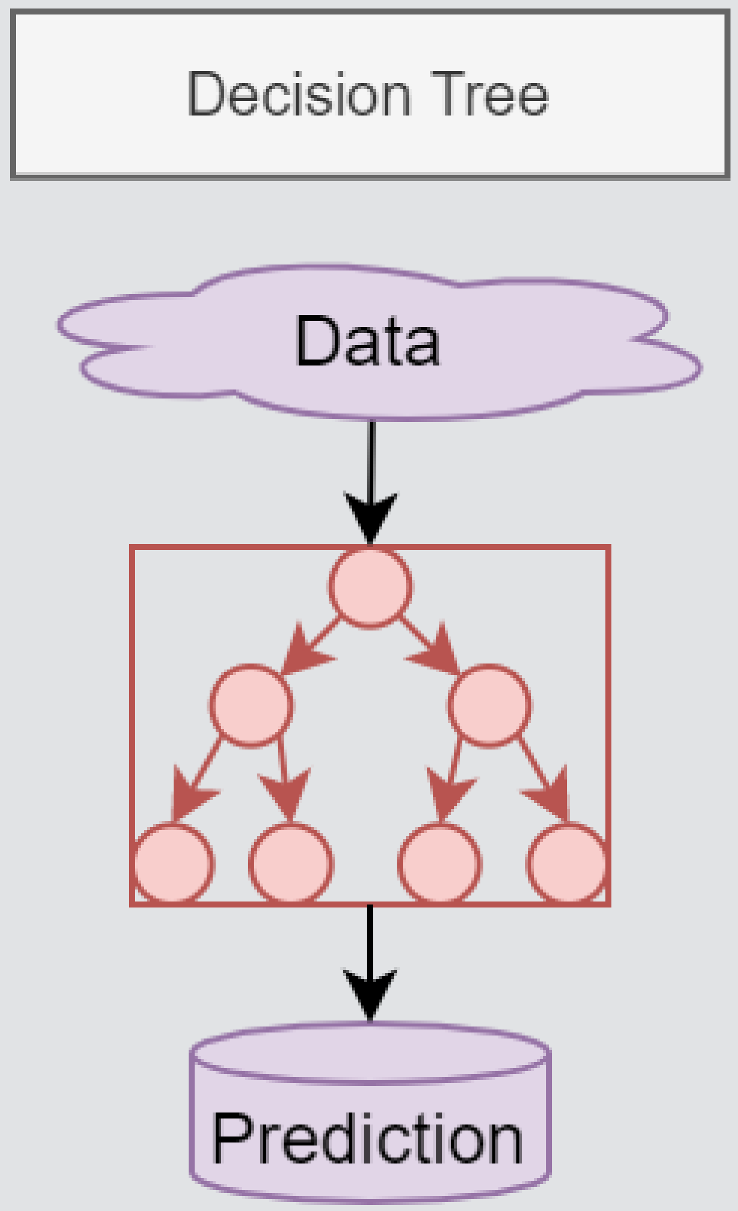
You need to do this in order to be able to predict with the model

- The `svm_final` object can be used with the standard `predict()` function
  - The `svm_fit_tuned` object could not!

Tree-based models

Simplest model: Decision tree

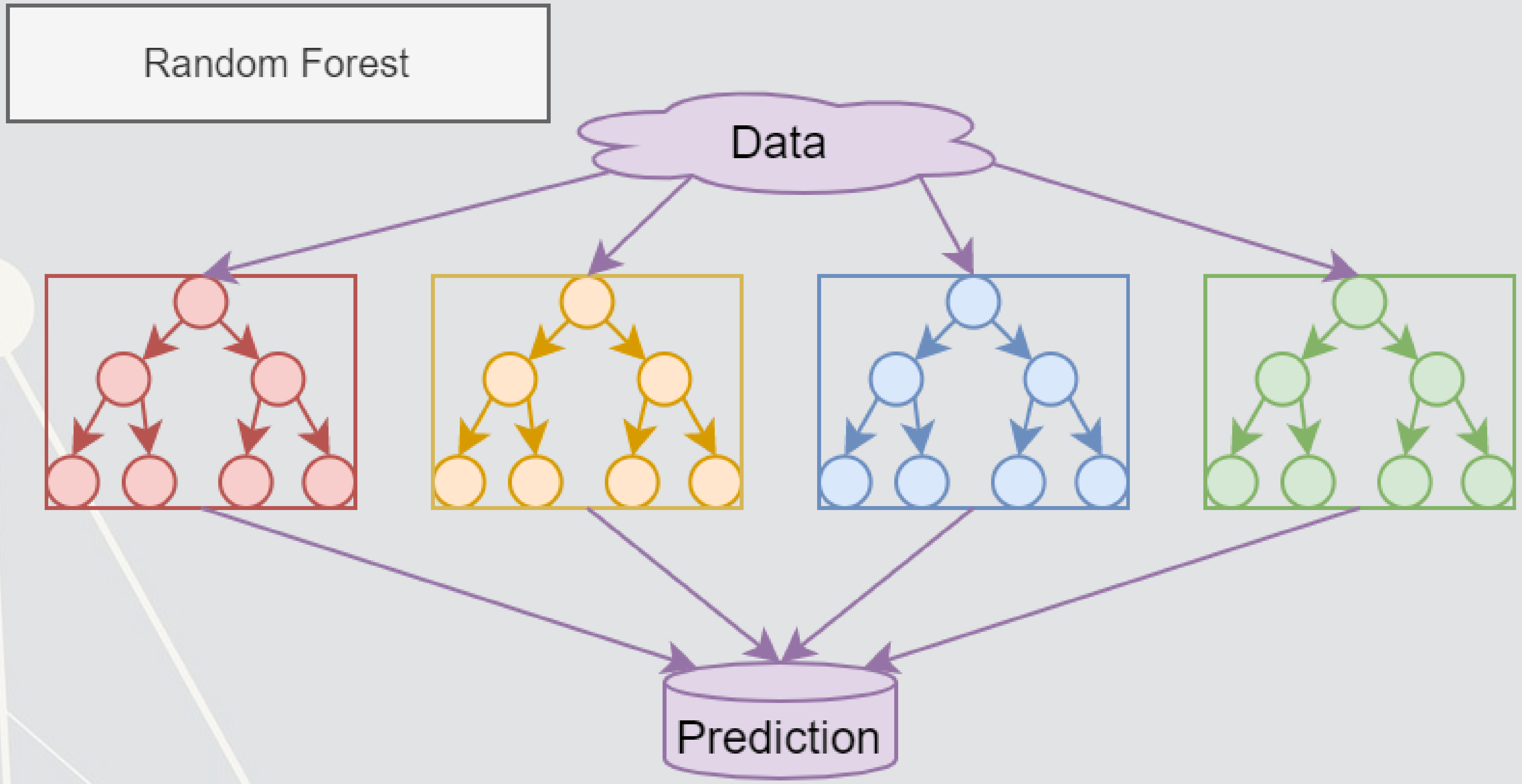
- A simple decision tree behaves as we saw in Mullainathan and Spiess (2017 JEP)
- It provides a set of conditions to traverse to go from data to the estimated output
- In order to capture a complex problem, many layers are needed



Simple model: Random Forest

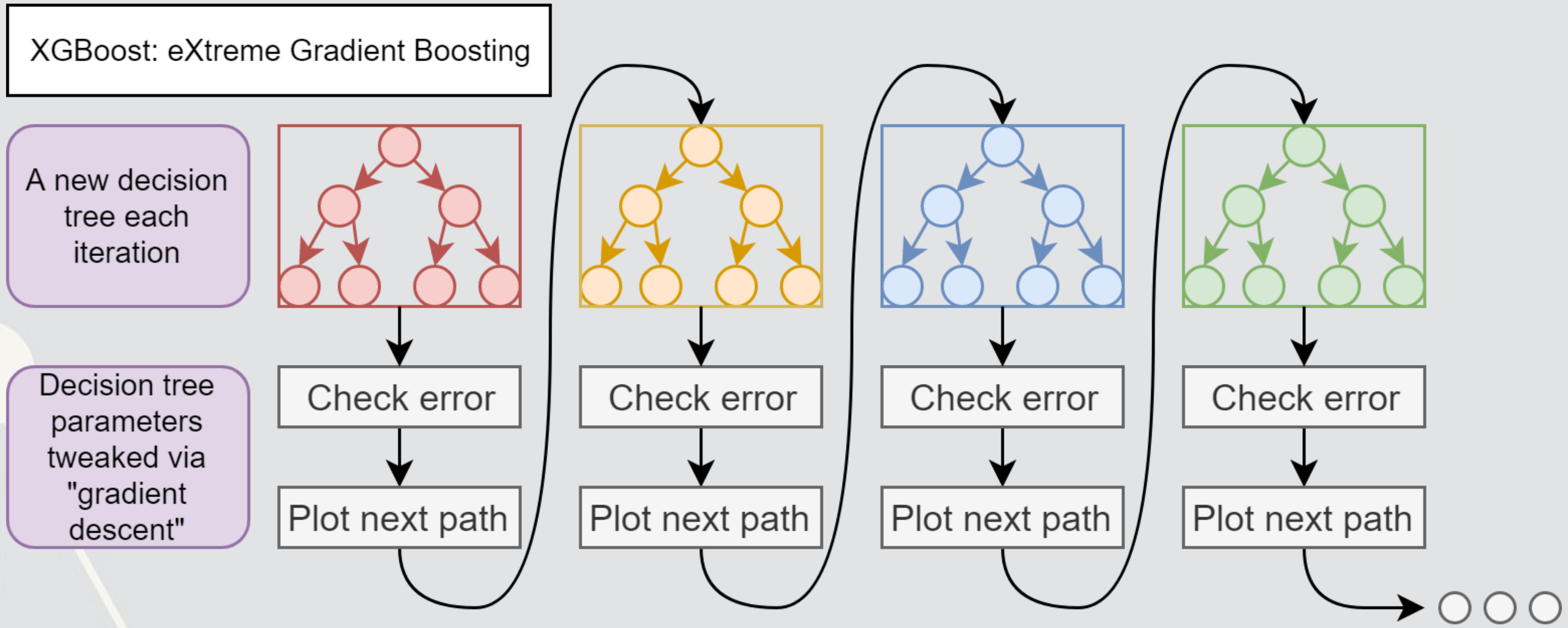
- 1 decision tree is OK, but…
  - There is a lot of error unless the tree is complex
  - Successive iterations of trees can be very different from one another

> Run a bunch of decision trees with less depth each and average them (but don’t give them all exactly the same data)



What is XGBoost

- e**X**treme **G**radient **B**oosting
- A simple explanation:
  1. Start with 1 or more decision trees & check error
  2. Make more decision trees & check error
  3. Use the difference in error to guess a another model
  4. Repeat #2 and #3 until the model's error is stable



XGBoost: Foundations

- XGBoost has its roots in AdaBoost (Adaptive Boosting)
  - Adaboost uses a sequence of weak learners to build a model
    - Combats against overfitting, and the sequence of individually weak models converges to be a strong learner
      - The convergence part is mathematically proven!
  - XGBoost isn’t as theoretically founded as Adaboost’
    - It trades off some mathematical rigor for flexibility and empirical performance

Benefits of XGBoost

- Tree based
  - Inherently non-parametric (no assumptions on data distribution)
- Non-linear but still somewhat interpretable
- Robust to noise
- Can handle missing or categorical variables (R implementation only)
- Robust to overfitting (somewhat)

As compared to other tree algorithms

- Implements gradient descent to sequentially grow trees
- Parallelizable (so it can be computed efficiently)
- Supports regularization

Drawbacks of XGBoost

So

many

hyperparameters.

- This makes it difficult to train a model well
  - But it is hard to beat a well trained XGBoost model with anything else we have discussed thus far
- It may technically be interpretable, but interpreting a big model is still difficult
- Like most tree-based methods, it struggles with extrapolation that is outside the bounds of its input data.

XGBoost parameters

```python
param = {
    'booster': 'gbtree',                # default -- tree based
    'nthread': 8,                       # number of threads to use for parallel processing
    'objective': 'binary:logistic',     # binary, output probabilities
    'eval_metric': 'auc',               # maximize ROC AUC
    'eta': 0.3,                         # shrinkage; [0, 1], default 0.3
    'max_depth': 6,                     # maximum depth of each tree; default 6
    'gamma': 0.1,                       # set above 0 to prune trees, [0, inf], default 0
    'min_child_weight': 1,              # higher leads to more pruning of tress, [0, inf], default 1
    'subsample': 0.8,                   # Randomly subsample rows if in (0, 1), default 1
    'colsample_bytree': 0.8,            # Randomly subsample variables if in (0, 1), default 1
    'random_state': 70
}
num_round = 30
```

A lot of parameters – we can optimize all from `eta` to `colsample_bytree` and the number of rounds

Running XGBoost

- We use `xgb.train()` to fit the model

```python
dtrain = xgb.DMatrix(train_X_logistic, label=train_Y_logistic, feature_names=vars_logistic)
dtest = xgb.DMatrix(test_X_logistic, label=test_Y_logistic, feature_names=vars_logistic)

model_xgb_logistic = xgb.train(param, dtrain, num_round)
```

```python
test_Yhat_xgb_logistic = model_xgb_logistic.predict(dtest
auc = metrics.roc_auc_score(test_Y_logistic, test_Yhat_xgb
print('AUC is {}'.format(auc))
```

```r
print('AUC is 0.6040163976960199')
```

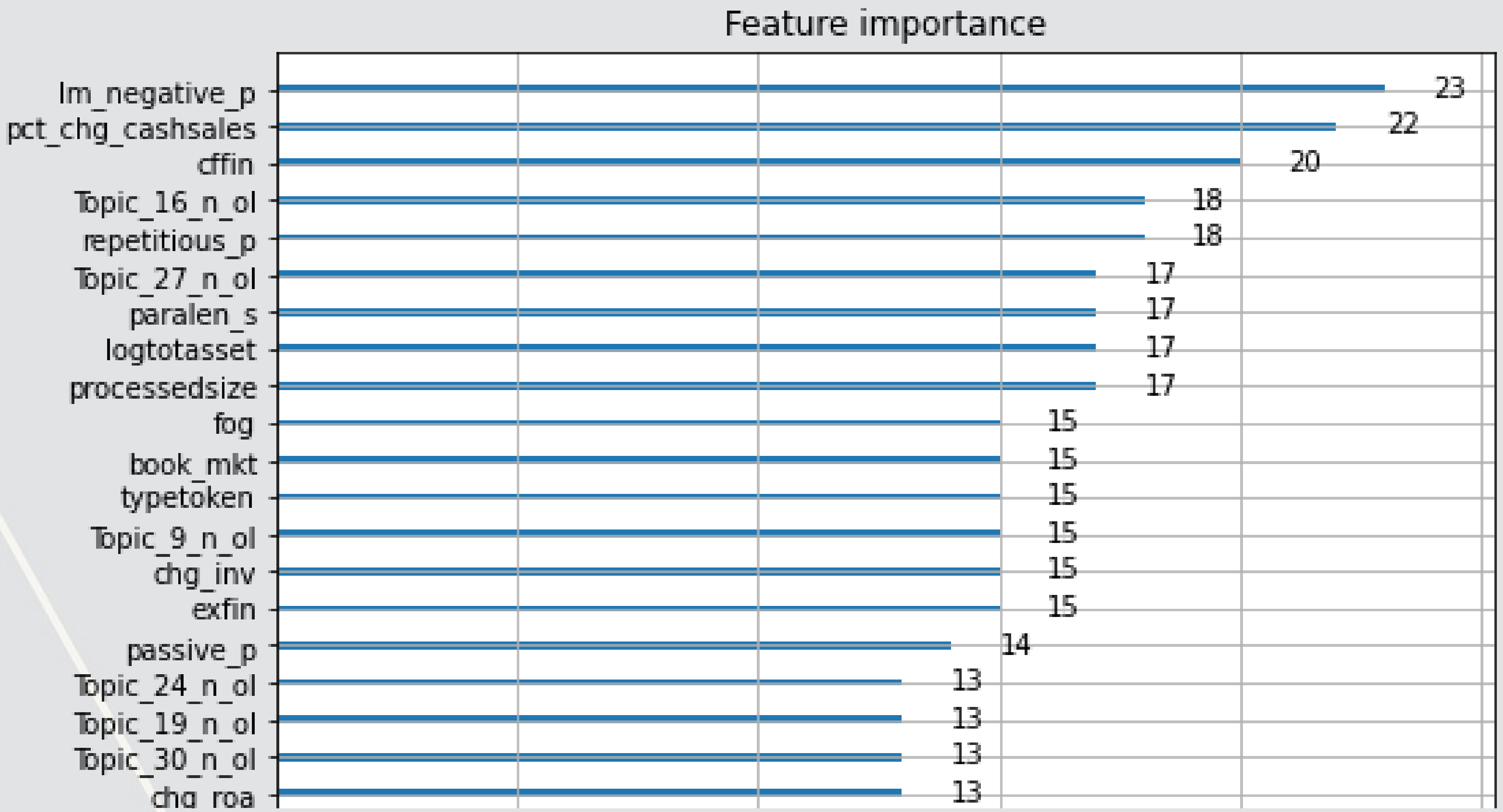
```
## [1] "AUC is 0.6040163976960199"
```

```python
fpr, tpr, thresholds = metrics.roc_curve(test_Y_logisti
display = metrics.RocCurveDisplay(fpr=fpr, tpr=tpr, roc_a
display.plot()
```

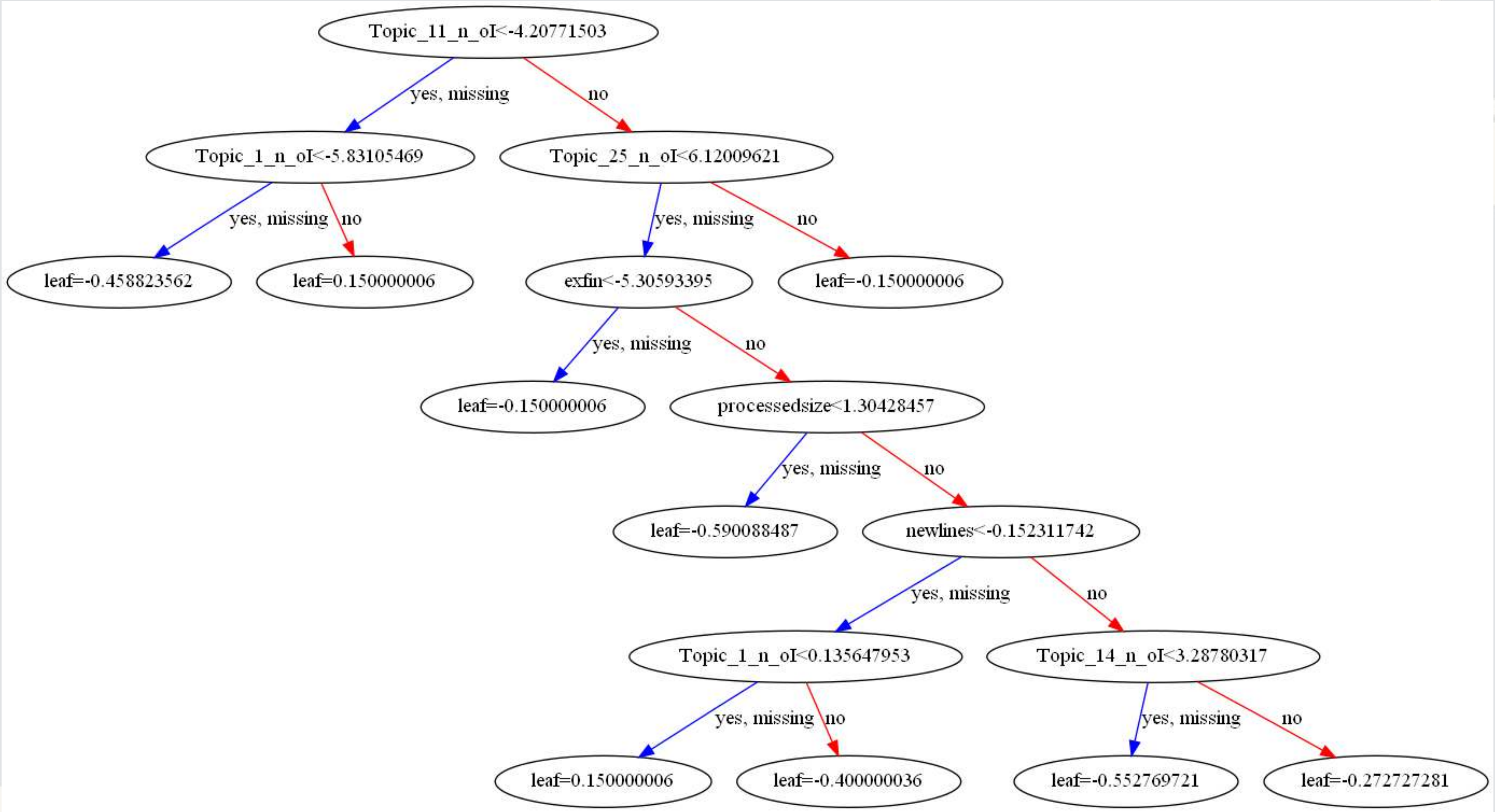
Analyzing the model: Importance plot

- The importance plot shows which variables have the greatest impact on the model
  - A higher number = more important
- In this case, we see a mix of sentiment, financial, topic, and grammatical measures in the top 5 measures

```python
fig, ax = plt.subplots(figsize=(8,16))
xgb.plot_importance(model_xgb_logistic, ax=ax)
```



Analyzing the model: Seeing the trees



One of 30 trees in the model

What about optimizing all the parameters?

> This can be done – details are in the python code file

Using R to run XGBoost

- The same package, `xgboost` works for this in R
  - The level of support across R and python is more or less the same

XGBoost in python

- Can solve numeric problems well
- Can do GPU computations for some models
- Can run larger-than-memory computations
  - Good for big data sets!

XGBoost in R

- Can solve numeric problems well
- Can also handle categorical inputs

- Use `tidymodels` just like we did for SVM, but specify `tune()` for each parameter you want to tune

Running CV XGBoost in R

```r
# model setup
params <- list(max_depth=10,
               eta=0.2,
               gamma=10,
               min_child_weight = 5,
               objective =
                 "binary:logistic")

# run the model
xgbCV <- xgb.cv(params=params,
                data=train_x,
                label=train_y,
                nrounds=100,
                eval_metric="auc",
                nfold=10,
                stratified=TRUE)
```

Conclusion

Wrap-up

SVM: Support Vector Machine

- Good for classification
- Can be good for regression in some contexts
- Key: Optimizes separability under some tolerance for error

Tree models

- Strong classification performance
- Can handle sparsity well
- A somewhat interpretable yet non-linear class of models

Packages used for these slides

Python

- matplotlib
- numpy
- pandas
- scikit-learn
- xgboost
- umap-learn

R

- caret
- kableExtra
- kernlab
- knitr
- reticulate
- revealjs
- ROCR
- tidymodels
- tidyverse
- xgboost

References

- Chen, Tianqi, and Carlos Guestrin. “Xgboost: A scalable tree boosting system.” In Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining, pp. 785-794. 2016.
- Deryugina, Tatyana, Garth Heutel, Nolan H. Miller, David Molitor, and Julian Reif. “The mortality and medical costs of air pollution: Evidence from changes in wind direction.” American Economic Review 109, no. 12 (2019): 4178-4219.
- Mullainathan, Sendhil, and Jann Spiess. “Machine learning: an applied econometric approach.” Journal of Economic Perspectives 31, no. 2 (2017): 87-106.
- Purda, Lynnette, and David Skillicorn. “Accounting variables, deception, and a bag of words: Assessing the tools of fraud detection.” Contemporary Accounting Research 32, no. 3 (2015): 1193-1223.

Custom code

```python
# Replication of R's coefplot function for use with sklearn's linear and logistic LASSO

def coefplot(names, coef, title=None):
    # Make sure coef is list, cast to list if needed.
    if isinstance(coef, np.ndarray):
        if len(coef.shape) > 1:
            coef = list(coef[0])
        else:
            coef = list(coef)

    # Drop unneeded vars
    data = []
    for i in range(0, len(coef)):
        if coef[i] != 0:
            data.append([names[i], coef[i]])
    data.sort(key=lambda x: x[1])

    # Add in a key for the plot axis
    data = [data[i] + [i+1] for i in range(0,len(data))]

    fig, ax = plt.subplots(figsize=(4,0.25*len(data)))

    ax.scatter([i[1] for i in data], [i[2] for i in data])

    ax.grid(axis='y')
    ax.set(xlabel="Fitted value", ylabel="Residual", title=(title if title is not None else "Coefficient Plot"))

    ax.axvline(x=0, linestyle='dotted')
    ax.set_yticks([i[2] for i in data])
    ax.set_yticklabels([i[0] for i in data])

    return ax
```