Preprocessing

Presented by Yasin Ceran

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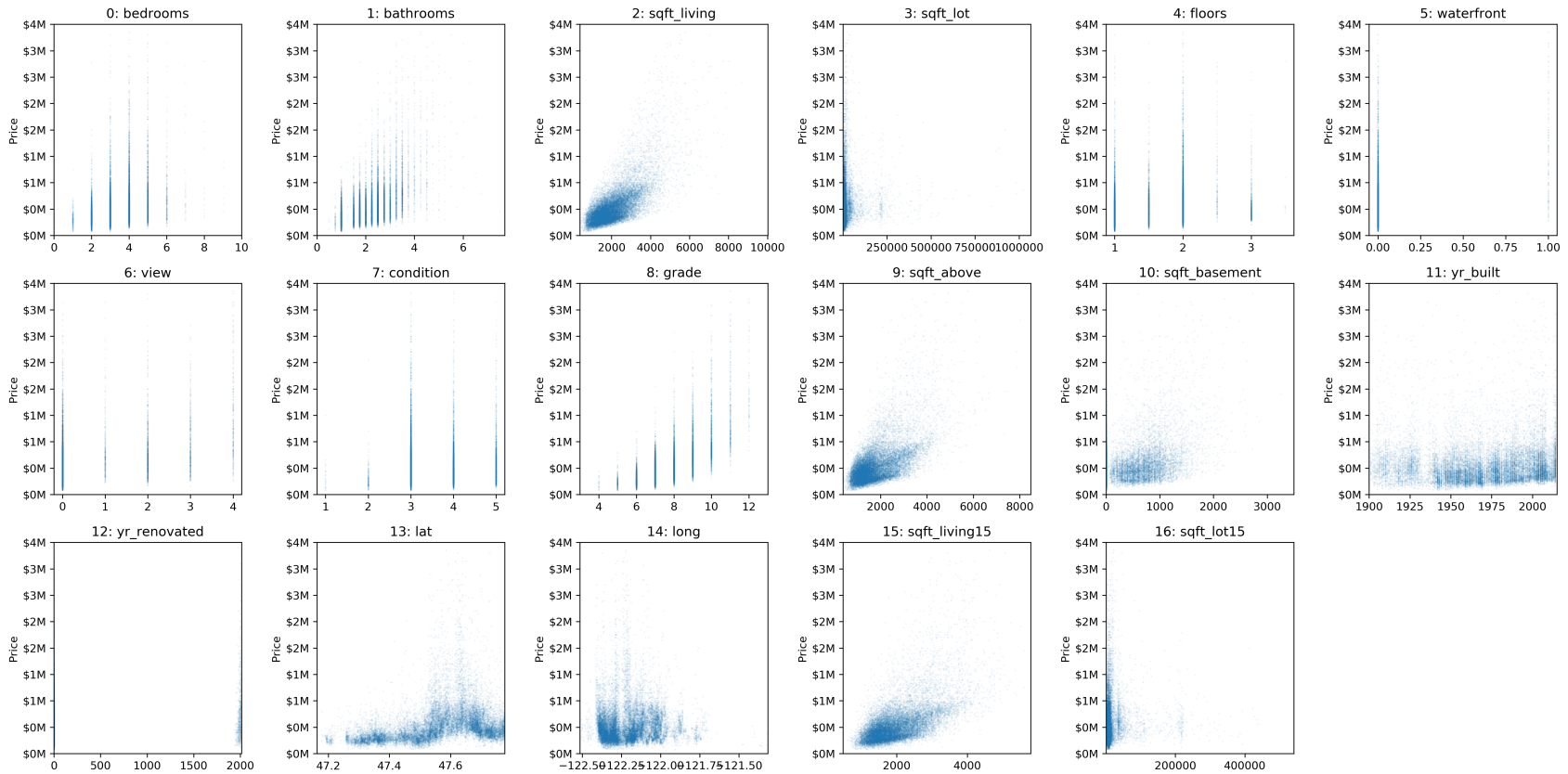
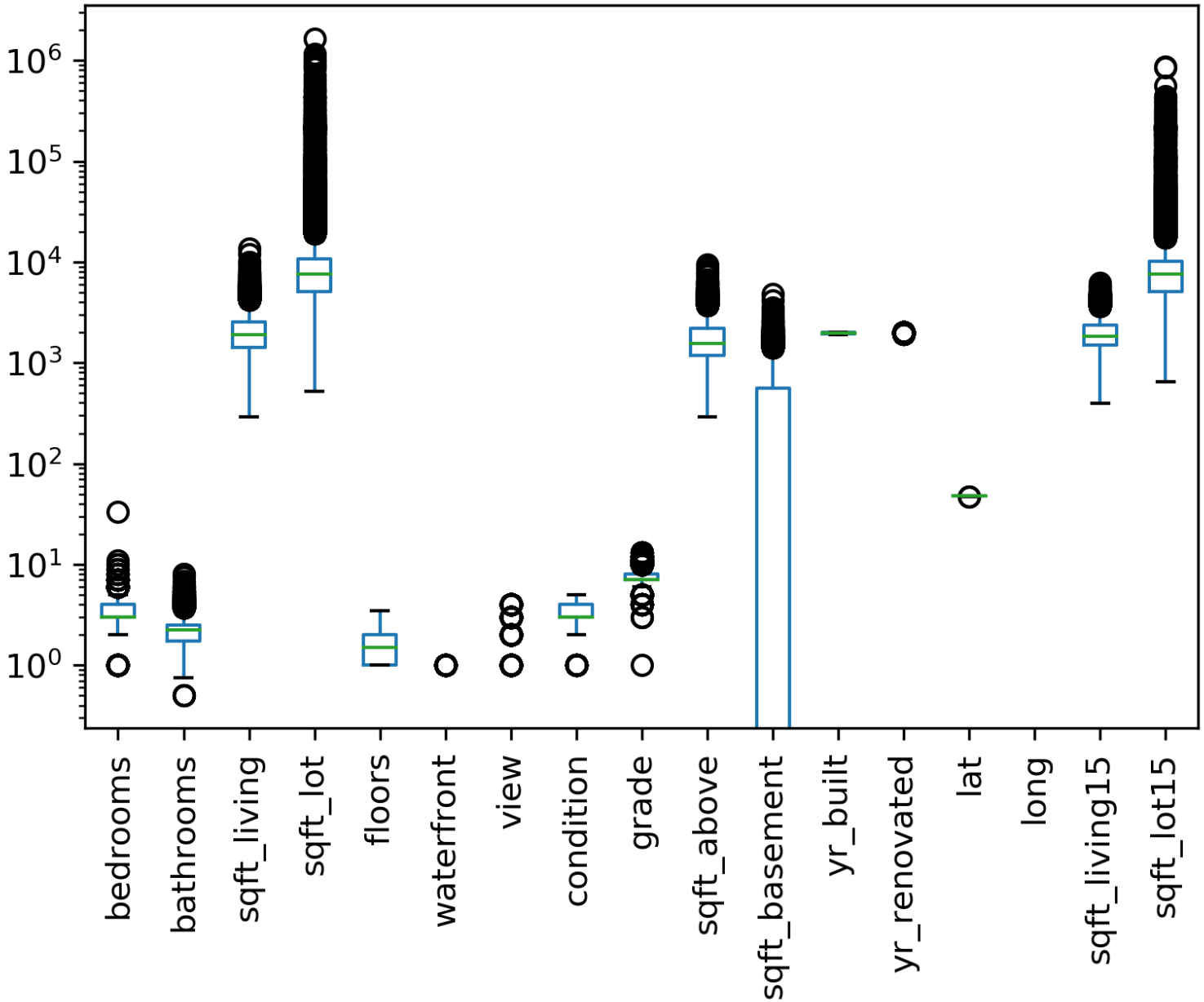
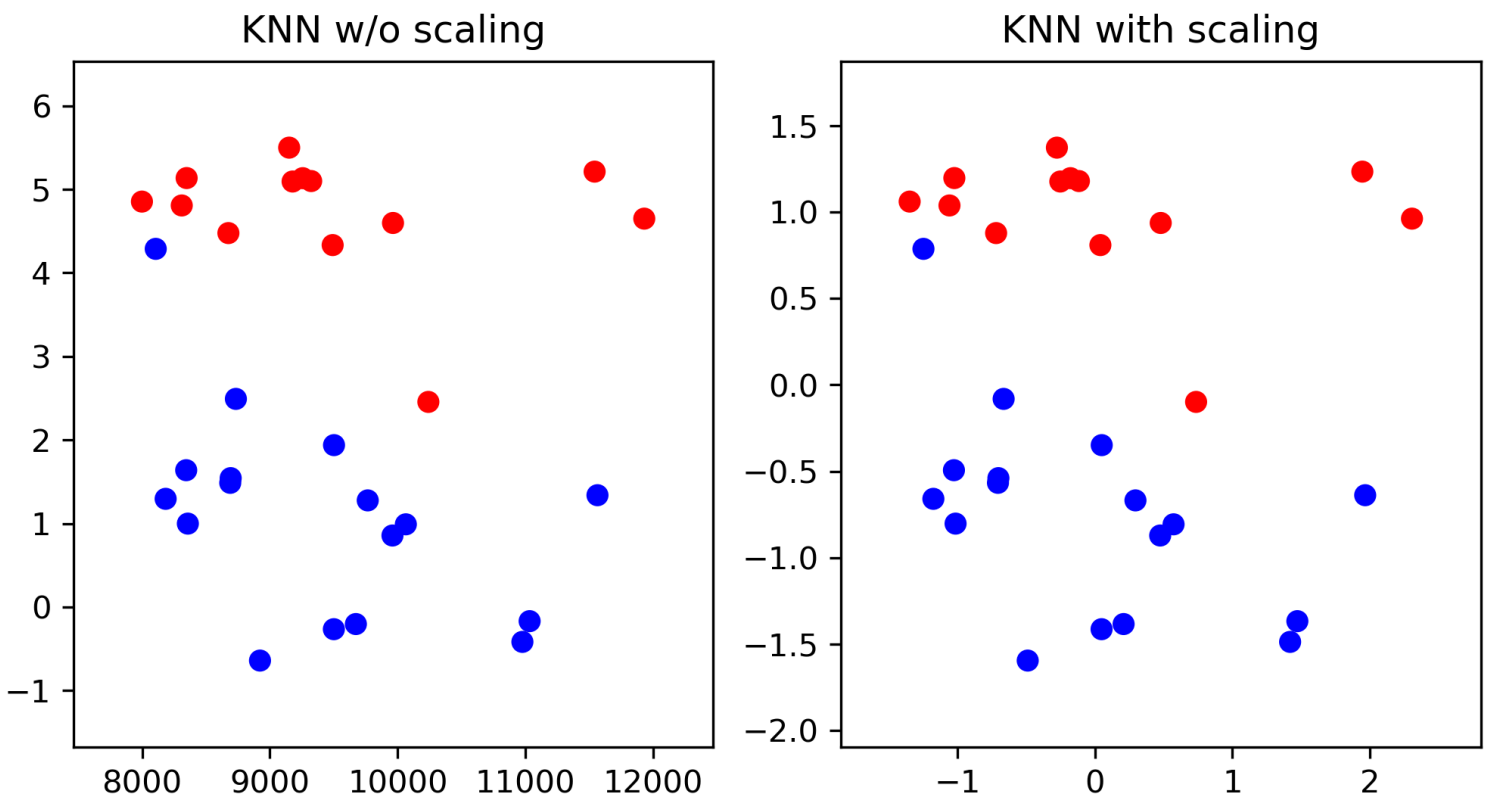
Scatter Plot of King County House Data



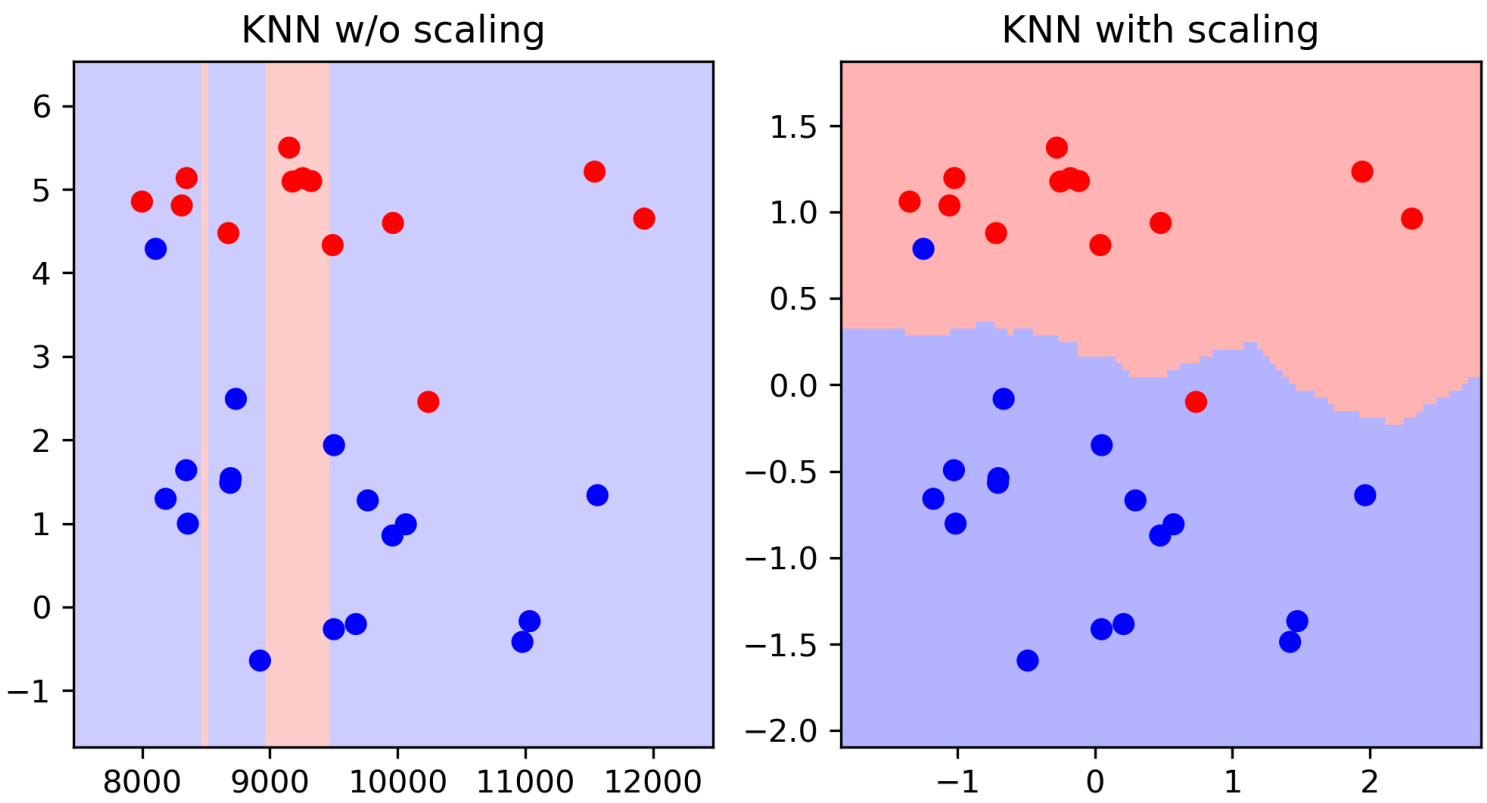
Box Plot of King County House Data



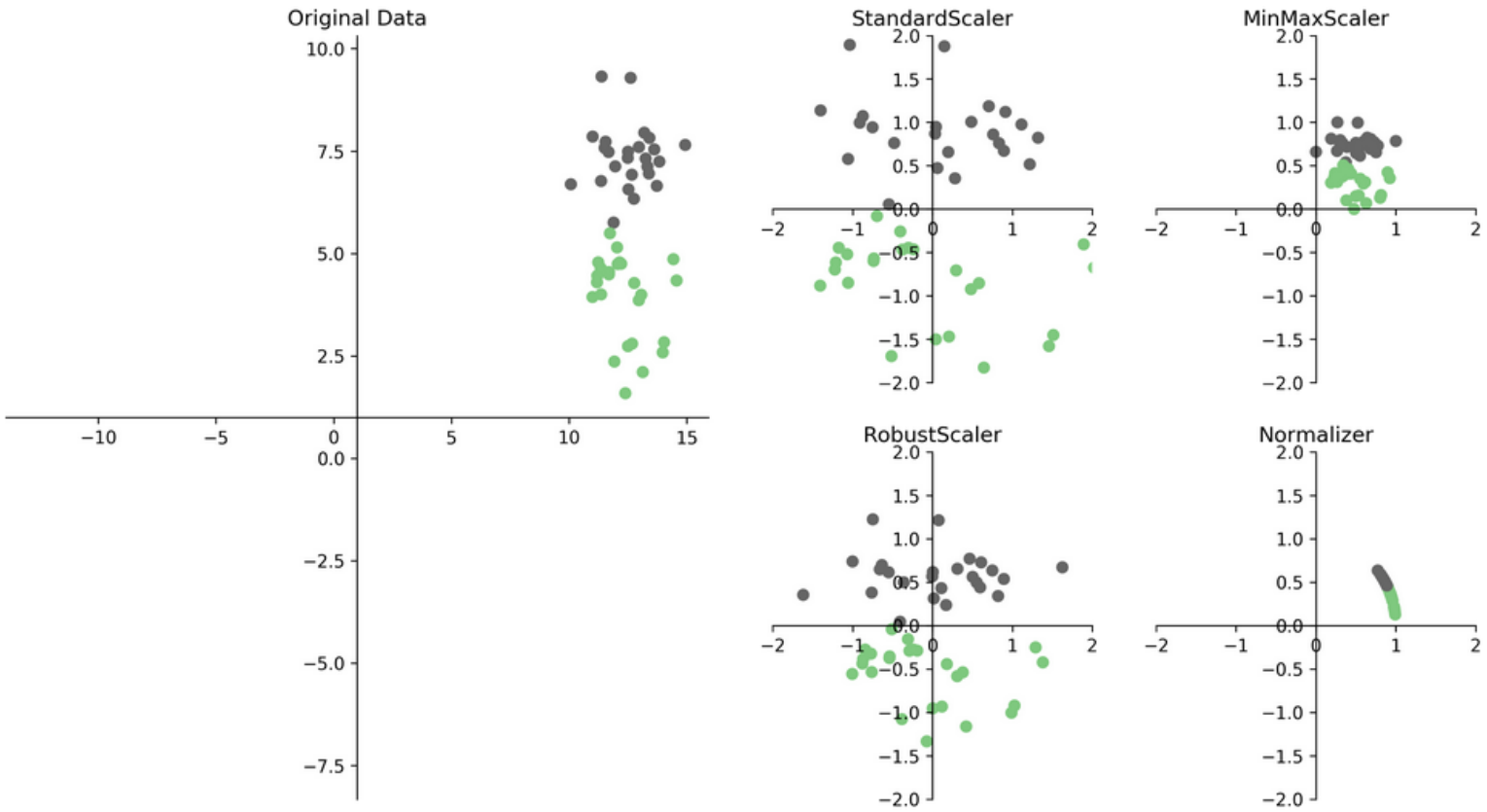
Scaling and Distances



Scaling and Distances



Ways to Scale



Sparse Data

- Data with many zeros – only store non-zero entries.
- Subtracting anything will make the data "dense" (no more zeros) and blow the RAM.
- Only scale, don't center (use MaxAbsScaler)

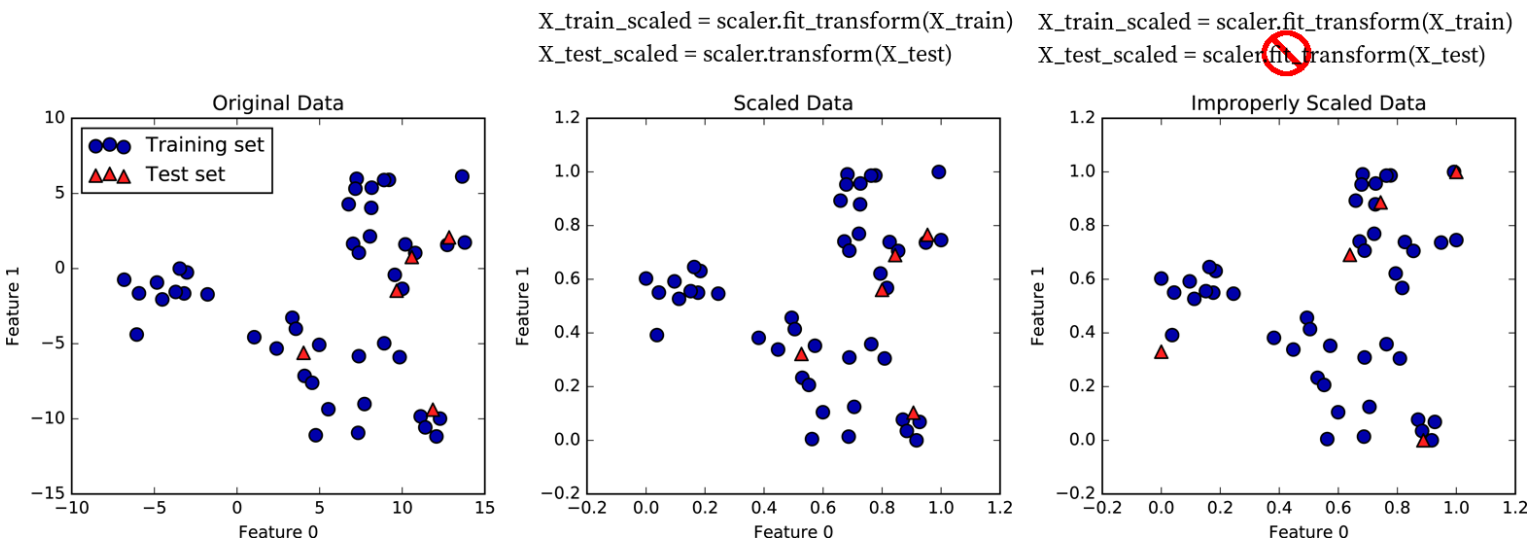
Standard Scaler Example

```
# Back to King Country house prices
X_train, X_test, y_train, y_test = train_test_split(
    X, y, random_state=0)

scaler = StandardScaler()
scaler.fit(X_train)
X_train_scaled = scaler.transform(X_train)

ridge = Ridge().fit(X_train_scaled, y_train)
X_test_scaled = scaler.transform(X_test)
ridge.score(X_test_scaled, y_test)

0.684
```



Sckit-Learn API Summary

estimator.fit(X, [y])

estimator.predict	estimator.transform
Classification	Preprocessing
Regression	Dimensionality reduction
Clustering	Feature selection
	Feature extraction

```
1
2 # Efficient Shortcuts:
3
4 est.fit_transform(X) == est.fit(X).transform(X)  # mostly
5 est.fit_predict(X) == est.fit(X).predict(X)   # mostly
```

Scaling In Action

```
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import RidgeCV
scores = cross_val_score(RidgeCV(), X_train, y_train, cv=10)
np.mean(scores), np.std(scores)

(0.694, 0.027)
```

```
scores = cross_val_score(RidgeCV(), X_train_scaled, y_train, cv=10)
np.mean(scores), np.std(scores)

(0.694, 0.027)
```

```
scores = cross_val_score(KNeighborsRegressor(), X_train, y_train, cv=10)
np.mean(scores), np.std(scores)

(0.500, 0.039)
```

```
scores = cross_val_score(KNeighborsRegressor(), X_train_scaled, y_train, cv=10)
np.mean(scores), np.std(scores)

(0.786, 0.030)
```

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A common Error

```
print(X.shape)

(100, 10000)
```

```
# select most informative 5% of features
from sklearn.feature_selection import SelectPercentile, f_regression
select = SelectPercentile(score_func=f_regression, percentile=5)
select.fit(X, y)
X_selected = select.transform(X)
print(X_selected.shape)

(100, 500)
```

```
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import Ridge
np.mean(cross_val_score(Ridge(), X_selected, y))

0.90
```

```
ridge = Ridge().fit(X_selected, y)
X_test_selected = select.transform(X_test)
ridge.score(X_test_selected, y_test)

-0.18
```

A Common Error: Leaking Information

```python
# BAD!
select.fit(X, y)  # includes the cv test parts!
X_sel = select.transform(X)
scores = []
for train, test in cv.split(X, y):
    ridge = Ridge().fit(X_sel[train], y[train])
    score = ridge.score(X_sel[test], y[test])
    scores.append(score)
```

```python
# GOOD!
scores = []
for train, test in cv.split(X, y):
    select.fit(X[train], y[train])
    X_sel_train = select.transform(X[train])
    ridge = Ridge().fit(X_sel_train, y[train])
    X_sel_test = select.transform(X[test])
    score = ridge.score(X_sel_test, y[test])
    scores.append(score)
```

Need to include preprocessing in cross-validation !

Scaling with Pipeline

```
# Housing data example
from sklearn.linear_model import Ridge
X, y = df, target

scaler = StandardScaler()
scaler.fit(X_train)
X_train_scaled = scaler.transform(X_train)
ridge = Ridge().fit(X_train_scaled, y_train)

X_test_scaled = scaler.transform(X_test)
ridge.score(X_test_scaled, y_test)

0.684
```

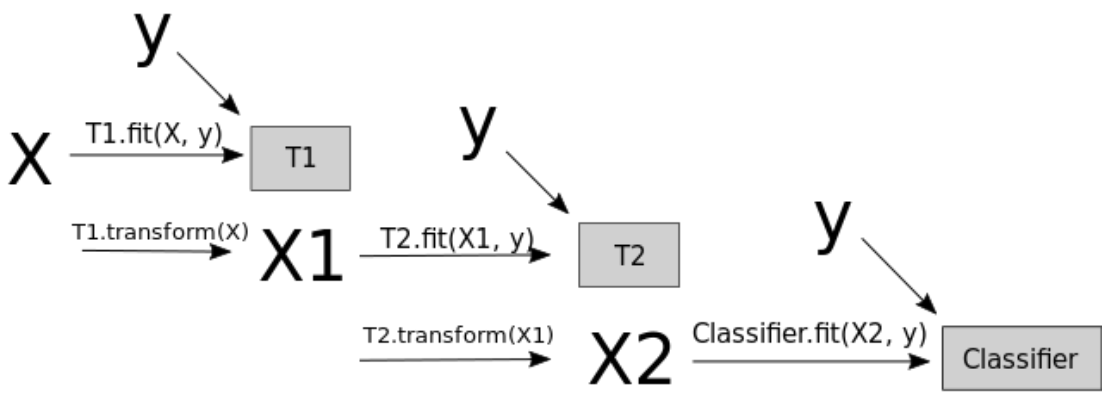
```
from sklearn.pipeline import make_pipeline
pipe = make_pipeline(StandardScaler(), Ridge())
pipe.fit(X_train, y_train)
pipe.score(X_test, y_test)

0.684
```

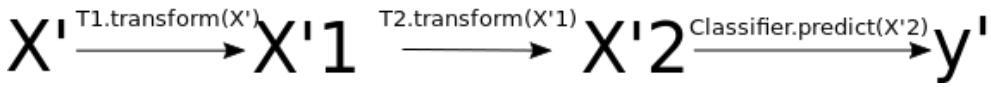
Pipeline

```
pipe = make_pipeline(T1(), T2(), Classifier())
```


```
pipe.fit(X, y)
```




```
pipe.predict(X')
```



Correcting Our Previous Error

```
# BAD!
select.fit(X, y)  # includes the cv test parts!
X_sel = select.transform(X)
scores = []
for train, test in cv.split(X, y):
    ridge = Ridge().fit(X_sel[train], y[train])
    score = ridge.score(X_sel[test], y[test])
    scores.append(score)
```

Same as:

```
select.fit(X, y)
X_selected = select.transform(X, y)
np.mean(cross_val_score(Ridge(), X_selected, y))

0.90
```

```
# GOOD!
scores = []
for train, test in cv.split(X, y):
    select.fit(X[train], y[train])
    X_sel_train = select.transform(X[train])
    ridge = Ridge().fit(X_sel_train, y[train])
    X_sel_test = select.transform(X[test])
    score = ridge.score(X_sel_test, y[test])
    scores.append(score)
```

Same as:

```
pipe = make_pipeline(select, Ridge())
np.mean(cross_val_score(pipe, X, y))

-0.079
```

Naming Steps

```

from sklearn.pipeline import make_pipeline
knn_pipe = make_pipeline(StandardScaler(), KNeighborsRegressor())
print(knn_pipe.steps)

[('standardscaler', StandardScaler()),
 ('kneighborsregressor', KNeighborsRegressor())]
```

```

from sklearn.pipeline import Pipeline
pipe = Pipeline([("scaler", StandardScaler()),
                 ("regressor", KNeighborsRegressor())])
```

Pipeline and GridSearchCV

```
1
2
3  from sklearn.model_selection import GridSearchCV
4
5  knn_pipe = make_pipeline(StandardScaler(), KNeighborsRegressor())
6  param_grid = {'kneighborsregressor__n_neighbors': range(1, 10)}
7  grid = GridSearchCV(knn_pipe, param_grid, cv=10)
8  grid.fit(X_train, y_train)
9  print(grid.best_params_)
10 print(grid.score(X_test, y_test))
11
12 {'kneighborsregressor__n_neighbors': 7}
13 0.60
```

Going Wild with Pipeline

```
1
2
3  from sklearn.datasets import load_diabetes
4  diabetes = load_diabetes()
5  X_train, X_test, y_train, y_test = train_test_split(
6      diabetes.data, diabetes.target, random_state=0)
7
8  from sklearn.preprocessing import PolynomialFeatures
9  pipe = make_pipeline(
10     StandardScaler(),
11     PolynomialFeatures(),
12     Ridge())
13
14 param_grid = {'polynomialfeatures__degree': [1, 2, 3],
15                'ridge__alpha': [0.001, 0.01, 0.1, 1, 10, 100]}
16 grid = GridSearchCV(pipe, param_grid=param_grid,
17                     n_jobs=-1, return_train_score=True)
18 grid.fit(X_train, y_train)
```

Going Wilder with Pipeline

```
1
2
3  pipe = Pipeline([('scaler', StandardScaler()),
4                   ('regressor', Ridge())])
5
6  param_grid = {'scaler': [StandardScaler(), MinMaxScaler(),
7                           'passthrough'],
8                'regressor': [Ridge(), Lasso()],
9                'regressor__alpha': np.logspace(-3, 3, 7)}
10
11
12 grid = GridSearchCV(pipe, param_grid)
13 grid.fit(X_train, y_train)
14 grid.score(X_test, y_test)
```

Going Wildest with Pipeline

```
1
2
3  from sklearn.tree import DecisionTreeRegressor
4  pipe = Pipeline([('scaler', StandardScaler()),
5                   ('regressor', Ridge())])
6
7  # check out searchgrid for more convenience
8  param_grid = [{'regressor': [DecisionTreeRegressor()],
9                 'regressor__max_depth': [2, 3, 4],
10                'scaler': ['passthrough']},
11               {'regressor': [Ridge()],
12                'regressor__alpha': [0.1, 1],
13                'scaler': [StandardScaler(), MinMaxScaler(),
14                           'passthrough']}
15              ]
16 grid = GridSearchCV(pipe, param_grid)
17 grid.fit(X_train, y_train)
18 grid.score(X_test, y_test)
```

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Dealing with missing values

- Missing values can be encoded in many ways
- Numpy has no standard format for it (often np.NaN) - pandas does
- Sometimes: 999, ???, ?, np.inf, “N/A”, “Unknown”...
- Not discussing “missing output” - that’s semi-supervised learning.
- Often missingness is informative (Use ‘MissingIndicator‘)

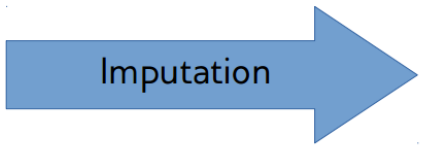
How Do Missing Values Look Like?

```
array([[ nan,  3.2,  5.7,  2.3],
       [ nan,  2.8,  4.9,  2. ],
       [ nan,  2.8,  6.7,  2. ],
       [ nan,  2.7,  4.9,  1.8],
       [ 6.7,  3.3,  5.7,  2.1],
       [ nan,  3.2,  6. ,  1.8],
       [ nan,  2.8,  4.8,  1.8],
       [ nan,  3. ,  4.9,  1.8],
       [ nan,  2.8,  5.6,  2.1],
       [ nan,  3. ,  5.8,  1.6],
       [ 7.4,  2.8,  6.1,  1.9],
       [ nan,  3.8,  6.4,  2. ],
       [ 6.4,  2.8,  5.6,  2.2],
       [ nan,  2.8,  5.1,  1.5],
       [ nan,  2.6,  5.6,  1.4],
       [ nan,  3. ,  6.1,  2.3],
       [ nan,  3.4,  5.6,  2.4],
       [ nan,  3.1,  5.5,  1.8],
       [ nan,  3. ,  4.8,  1.8],
       [ 6.9,  3.1,  5.4,  2.1],
       [ 6.7,  3.1,  5.6,  2.4],
       [ nan,  3.1,  5.1,  2.3],
       [ nan,  2.7,  5.1,  1.9],
       [ nan,  3.2,  5.9,  2.3],
       [ nan,  3.3,  5.7,  2.5],
       [ nan,  3. ,  5.2,  2.3],
       [ nan,  2.5,  5. ,  1.9],
       [ nan,  3. ,  5.2,  2. ],
       [ 6.2,  3.4,  5.4,  2.3],
       [ nan,  3. ,  5.1,  1.8]])
```

```
array([[ 5.1,  3.5,  1.4,  0.2],
       [ nan,  nan,  1.4,  0.2],
       [ 4.7,  3.2,  1.3,  0.2],
       [ 4.6,  3.1,  1.5,  0.2],
       [ 5. ,  3.6,  1.4,  0.2],
       [ nan,  nan,  nan,  nan],
       [ 4.6,  3.4,  1.4,  0.3],
       [ 5. ,  3.4,  1.5,  0.2],
       [ 4.4,  2.9,  1.4,  0.2],
       [ 4.9,  3.1,  1.5,  0.1],
       [ 5.4,  3.7,  1.5,  0.2],
       [ 4.8,  3.4,  1.6,  0.2],
       [ 4.8,  3. ,  1.4,  0.1],
       [ 4.3,  3. ,  1.1,  0.1],
       [ nan,  nan,  nan,  nan],
       [ 5.7,  4.4,  1.5,  0.4],
       [ 5.4,  3.9,  1.3,  0.4],
       [ 5.1,  3.5,  1.4,  0.3],
       [ 5.7,  3.8,  1.7,  0.3],
       [ 5.1,  3.8,  1.5,  0.3],
       [ 5.4,  3.4,  1.7,  0.2],
       [ 5.1,  3.7,  1.5,  0.4],
       [ 4.6,  3.6,  1. ,  0.2],
       [ 5.1,  nan,  nan,  nan],
       [ 4.8,  3.4,  1.9,  0.2],
       [ 5. ,  3. ,  1.6,  0.2],
       [ nan,  nan,  nan,  0.4],
       [ 5.2,  3.5,  1.5,  0.2],
       [ 5.2,  3.4,  1.4,  0.2],
       [ 4.7,  3.2,  1.6,  0.2]])
```

How Do Missing Values Look Like?

```
array([[ 6. ,  3.4,  4.5,  nan],
       [ 6.9,  3.1,  5.1,  2.3],
       [ 4.6,  3.2,  1.4,  nan],
       [ 5.1,  3.8,  1.5,  nan],
       [ 4.4,  2.9,  nan,  nan],
       [ 6.6,  2.9,  4.6,  1.3],
       [ 6.7,  3. ,  5.2,  2.3],
       [ 6.3,  3.3,  6. ,  2.5],
       [ 7.2,  3. ,  5.8,  1.6],
       [ 4.6,  3.4,  1.4,  nan],
       [ 5.2,  3.5,  1.5,  nan],
       [ 5.4,  3.4,  nan,  nan],
       [ 5.9,  3.2,  4.8,  1.8],
       [ 4.9,  3.1,  nan,  nan],
       [ 6.9,  3.2,  5.7,  2.3],
       [ 5.7,  3.8,  nan,  0.3],
       [ 5.3,  3.7,  1.5,  nan],
       [ 4.5,  2.3,  1.3,  nan],
       [ 6.5,  3. ,  5.5,  1.8],
       [ 6.2,  2.9,  4.3,  1.3],
       [ 6.4,  2.8,  5.6,  2.2],
       [ 6.1,  3. ,  4.6,  1.4],
       [ 6.2,  2.8,  4.8,  1.8],
       [ 4.9,  2.5,  4.5,  1.7],
       [ 6. ,  2.7,  5.1,  nan],
       [ 6.8,  3.2,  5.9,  2.3],
       [ 6. ,  2.9,  4.5,  1.5],
       [ 4.9,  2.4,  3.3,  1. ],
       [ 5.8,  2.7,  5.1,  nan],
       [ 5.5,  2.4,  3.8,  nan]])
```




```
array([[ 6. ,  3.4,  4.5,  1.6],
       [ 6.9,  3.1,  5.1,  2.3],
       [ 4.6,  3.2,  1.4,  0.2],
       [ 5.1,  3.8,  1.5,  0.3],
       [ 4.4,  2.9,  1.4,  0.2],
       [ 6.6,  2.9,  4.6,  1.3],
       [ 6.7,  3. ,  5.2,  2.3],
       [ 6.3,  3.3,  6. ,  2.5],
       [ 7.2,  3. ,  5.8,  1.6],
       [ 4.6,  3.4,  1.4,  0.3],
       [ 5.2,  3.5,  1.5,  0.2],
       [ 5.4,  3.4,  1.5,  0.4],
       [ 5.9,  3.2,  4.8,  1.8],
       [ 4.9,  3.1,  1.5,  0.1],
       [ 6.9,  3.2,  5.7,  2.3],
       [ 5.7,  3.8,  1.7,  0.3],
       [ 5.3,  3.7,  1.5,  0.2],
       [ 4.5,  2.3,  1.3,  0.3],
       [ 6.5,  3. ,  5.5,  1.8],
       [ 6.2,  2.9,  4.3,  1.3],
       [ 6.4,  2.8,  5.6,  2.2],
       [ 6.1,  3. ,  4.6,  1.4],
       [ 6.2,  2.8,  4.8,  1.8],
       [ 4.9,  2.5,  4.5,  1.7],
       [ 6. ,  2.7,  5.1,  1.6],
       [ 6.8,  3.2,  5.9,  2.3],
       [ 6. ,  2.9,  4.5,  1.5],
       [ 4.9,  2.4,  3.3,  1. ],
       [ 5.8,  2.7,  5.1,  1.9],
       [ 5.5,  2.4,  3.8,  1.1]])
```

Imputation Methods

- Mean / Median
- kNN
- Regression models

Baseline: Dropping Columns

```
24 from sklearn.model_selection import train_test_split, cross_val_score
25 X_train, X_test, y_train, y_test = train_test_split(X_, y, stratify=y)
26
27 nan_columns = np.any(np.isnan(X_train), axis=0)
28 X_drop_columns = X_train[:, ~nan_columns]
29 scores = cross_val_score(LogisticRegressionCV(v=5), X_drop_columns, y_train, cv=10)
30 np.mean(scores)
31
32 0.772
```

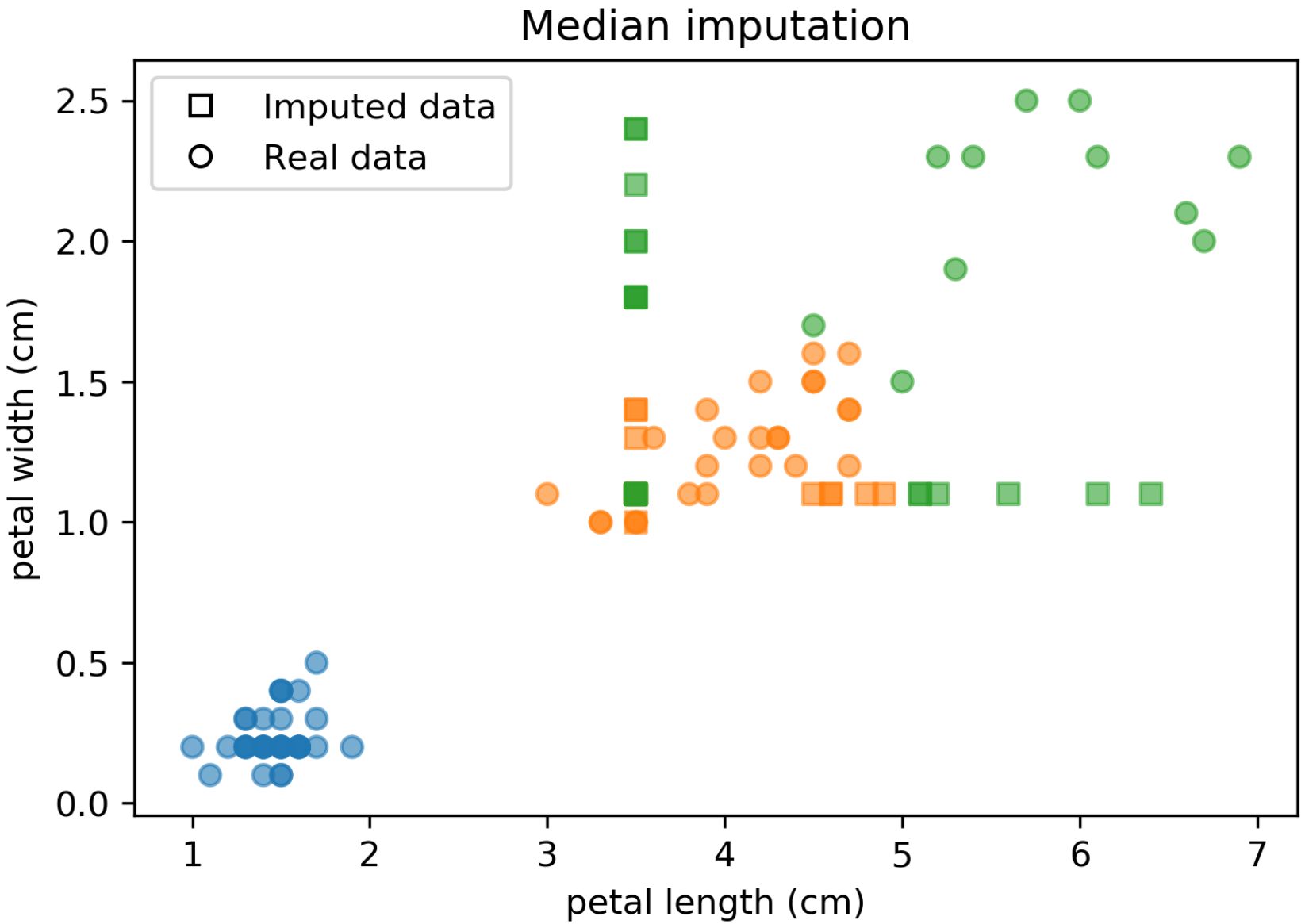
Mean and Median

```
[[ 6.   2.9  4.5  1.5]
 [ 5.9  3.   5.1  1.8]
 [ 4.4  3.   1.3  0.2]
 [ 5.1  3.3  nan  nan]
 [ 5.   3.5  1.6  0.6]
 [ 5.4  3.4  nan  nan]
 [ 5.7  3.8  nan  0.3]
 [ 5.6  2.5  3.9  nan]
 [ 7.7  2.6  6.9  2.3]
 [ 5.8  2.7  5.1  1.9]
 [ 6.7  3.1  5.6  2.4]
 [ 4.8  3.4  1.9  nan]
 [ 7.2  3.2  6.   1.8]
 [ 4.4  2.9  nan  nan]
 [ 6.9  3.2  5.7  2.3]
 [ 5.5  4.2  1.4  nan]
 [ 6.3  2.3  4.4  1.3]
 [ 7.   3.2  4.7  1.4]
 [ 5.8  2.7  nan  nan]
 [ 6.8  2.8  4.8  1.4]
 [ 5.4  3.9  1.7  nan]
 [ 7.6  3.   6.6  2.1]
 [ 7.7  2.8  6.7  2. ]
 [ 5.   3.3  nan  0.2]
 [ 5.9  3.   4.2  1.5]
 [ 6.1  2.8  4.   1.3]
 [ 5.   3.6  1.4  0.2]
 [ 7.4  2.8  6.1  1.9]
 [ 6.3  2.5  5.   1.9]
 [ 6.7  3.3  5.7  2.5]]
```

```
from sklearn.impute import SimpleImputer
imp = SimpleImputer(strategy="median").fit(X_train)
X_median_imp = imp.transform(X_train)
```


```
array([[ 6.   ,  2.9  ,  4.5  ,  1.5  ],
       [ 5.9  ,  3.   ,  5.1  ,  1.8  ],
       [ 4.4  ,  3.   ,  1.3  ,  0.2  ],
       [ 5.1  ,  3.3  ,  4.116,  1.462],
       [ 5.   ,  3.5  ,  1.6  ,  0.6  ],
       [ 5.4  ,  3.4  ,  4.116,  1.462],
       [ 5.7  ,  3.8  ,  4.116,  0.3  ],
       [ 5.6  ,  2.5  ,  3.9  ,  1.462],
       [ 7.7  ,  2.6  ,  6.9  ,  2.3  ],
       [ 5.8  ,  2.7  ,  5.1  ,  1.9  ],
       [ 6.7  ,  3.1  ,  5.6  ,  2.4  ],
       [ 4.8  ,  3.4  ,  1.9  ,  1.462],
       [ 7.2  ,  3.2  ,  6.   ,  1.8  ],
       [ 4.4  ,  2.9  ,  4.116,  1.462],
       [ 6.9  ,  3.2  ,  5.7  ,  2.3  ],
       [ 5.5  ,  4.2  ,  1.4  ,  1.462],
       [ 6.3  ,  2.3  ,  4.4  ,  1.3  ],
       [ 7.   ,  3.2  ,  4.7  ,  1.4  ],
       [ 5.8  ,  2.7  ,  4.116,  1.462],
       [ 6.8  ,  2.8  ,  4.8  ,  1.4  ],
       [ 5.4  ,  3.9  ,  1.7  ,  1.462],
       [ 7.6  ,  3.   ,  6.6  ,  2.1  ],
       [ 7.7  ,  2.8  ,  6.7  ,  2.   ],
       [ 5.   ,  3.3  ,  4.116,  0.2  ],
       [ 5.9  ,  3.   ,  4.2  ,  1.5  ],
       [ 6.1  ,  2.8  ,  4.   ,  1.3  ],
       [ 5.   ,  3.6  ,  1.4  ,  0.2  ],
       [ 7.4  ,  2.8  ,  6.1  ,  1.9  ],
       [ 6.3  ,  2.5  ,  5.   ,  1.9  ],
       [ 6.7  ,  3.3  ,  5.7  ,  2.5  ]])
```

Mean and Median-Graph



Baseline: Dropping Columns

```
33 from sklearn.preprocessing import StandardScalar
34
35 nan_columns = np.any(np.isnan(X_train), axis = 0)
36 X_drop_columns = X_train[:,~nan_columns]
37 logreg = make_pipeline(StandardScalar(), LogisticRegression())
38 scores = cross_val_score(logreg, X_drop_columns, y_train, cv=10)
39 np.mean(scores)
40
41 0.794
42
43 mean_pipe = make_pipeline(SimpleImputer(strategy='median'),
44                           StandardScalar(),
45                           LogisticRegression())
46 scores = cross_val_score(mean_pipe, X_train, y_train, cv=10)
47 np.mean(scores)
48
49 0.729
```

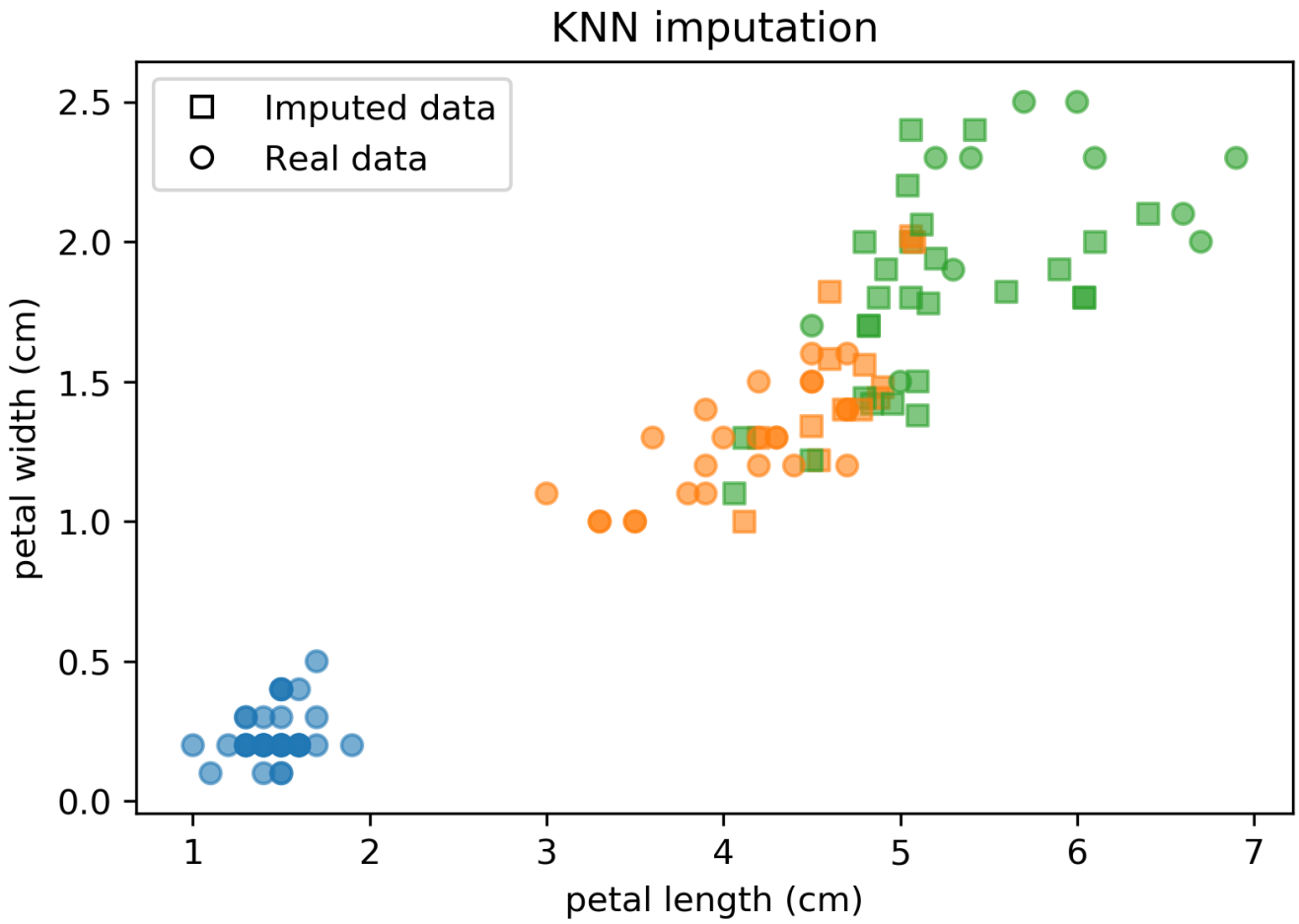
KNN Imputation

- Find k nearest neighbors that have non-missing values.
- Fill in all missing values using the average of the neighbors.

KNN Imputation-Code-Graph

```
knn_pipe = make_pipeline(KNNImputer(), StandardScaler(), LogisticRegression())
np.mean(scores)

0.849
```



Model-Driven Imputation

- Train regression model for missing values
- Iterate: retrain after filling in

```
rf_imp = IterativeImputer(predictor=RandomForestRegressor())
rf_pipe = make_pipeline(rf_imp, StandardScaler(), LogisticRegression())

scores = cross_val_score(rf_pipe, X_train, y_train, cv=10)
np.mean(scores)

0.845
```

Comparison of Imputation Methods

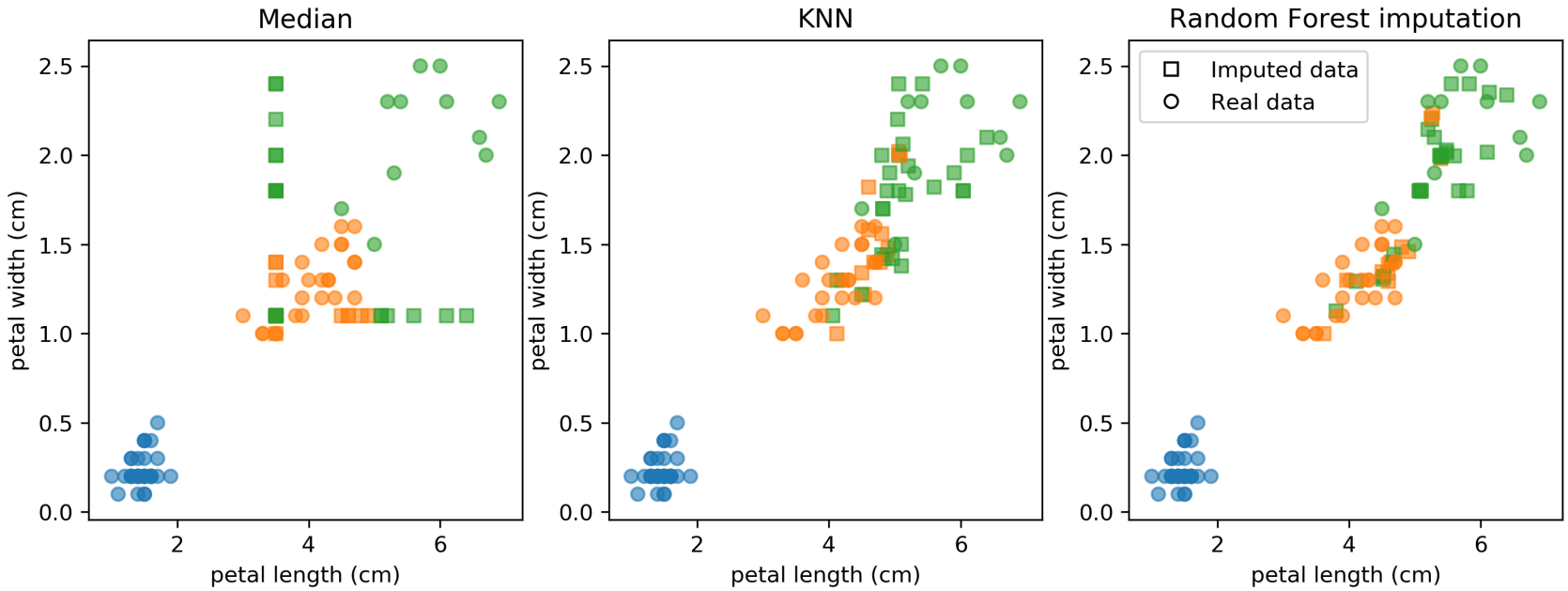


Table of Contents

Categorical Variables

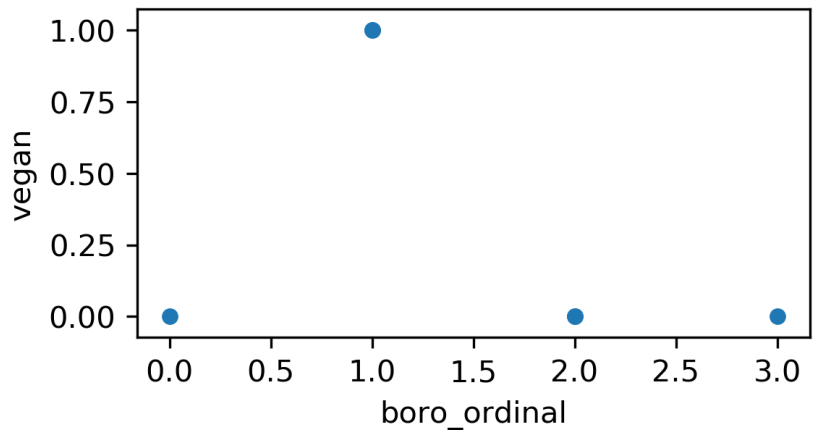
```
import pandas as pd
df = pd.DataFrame({
  'boro': ['Manhattan', 'Queens', 'Manhattan', 'Brooklyn', 'Brooklyn', 'Bronx'],
  'salary': [103, 89, 142, 54, 63, 219],
     'vegan': ['No', 'No','No','Yes', 'Yes', 'No']})
```

id	Boro	Salary	Vegan
0	Manhattan	103	No
1	Queens	89	No
2	Manhattan	142	No
3	Brooklyn	54	Yes
4	Brooklyn	63	Yes
5	Bronx	219	No

Ordinal Encoding

```
df['boro_ordinal'] = df.boro.astype("category").cat.codes
df
```

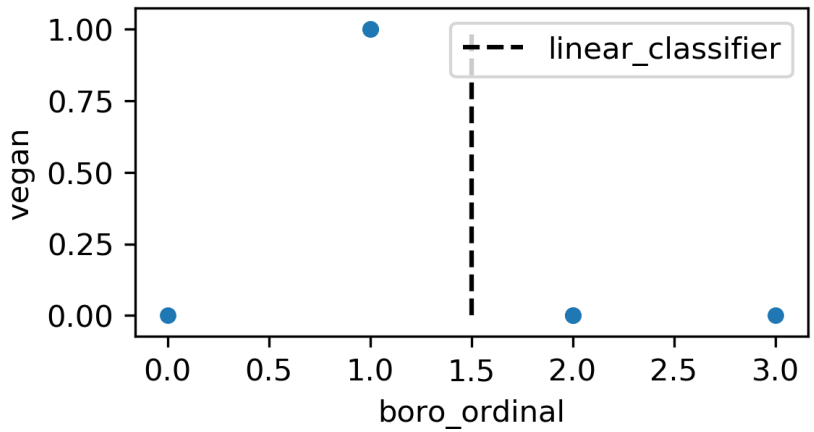
id	Boro	Salary	Vegan
0	2	103	No
1	3	89	No
2	2	142	No
3	1	54	Yes
4	1	63	Yes
5	0	219	No



Ordinal Encoding

```
df['boro_ordinal'] = df.boro.astype("category").cat.codes
df
```

id	Boro	Salary	Vegan
0	2	103	No
1	3	89	No
2	2	142	No
3	1	54	Yes
4	1	63	Yes
5	0	219	No



One-Hot (Dummy) Encoding

id	Boro	Salary	Vegan
0	Manhattan	103	No
1	Queens	89	No
2	Manhattan	142	No
3	Brooklyn	54	Yes
4	Brooklyn	63	Yes
5	Bronx	219	No

```
1 import pandas as pd
2 pd.get_dummies(df)
```

	salary	boro_Bronx	boro_Brooklyn	boro_Manhattan	boro_Queens	vegan_No	vegan_Yes
0	103	0	0	1	0	1	0
1	89	0	0	0	1	1	0
2	142	0	0	1	0	1	0
3	54	0	1	0	0	0	1
4	63	0	1	0	0	0	1
5	219	1	0	0	0	1	0

One-Hot (Dummy) Encoding

id	Boro	Salary	Vegan
0	Manhattan	103	No
1	Queens	89	No
2	Manhattan	142	No
3	Brooklyn	54	Yes
4	Brooklyn	63	Yes
5	Bronx	219	No

```
1 import pandas as pd
2 pd.get_dummies(df, columns=['boro'])
```

	salary	vegan	boro_Bronx	boro_Brooklyn	boro_Manhattan	boro_Queens
0	103	No	0	0	1	0
1	89	No	0	0	0	1
2	142	No	0	0	1	0
3	54	Yes	0	1	0	0
4	63	Yes	0	1	0	0
5	219	No	1	0	0	0

One-Hot (Dummy) Encoding

	Boro	Salary	Vegan
0	2	103	No
1	3	89	No
2	2	142	No
3	1	54	Yes
4	1	63	Yes
5	0	219	No

```
1 import pandas as pd
2 pd.get_dummies(df_ordinal, columns=['boro'])
```

	salary	vegan	boro_0	boro_1	boro_2	boro_3
0	103	No	0	0	1	0
1	89	No	0	0	0	1
2	142	No	0	0	1	0
3	54	Yes	0	1	0	0
4	63	Yes	0	1	0	0
5	219	No	1	0	0	0

One-Hot (Dummy) Encoding

```
df = pd.DataFrame({
                    'boro': ['Manhattan', 'Queens
    ', 'Manhattan',
             'Brooklyn', 'Brooklyn', 'Bronx'],
  'salary': [103, 89, 142, 54, 63, 219],
  'vegan': ['No', 'No','No','Yes', 'Yes', 'No'
      ]})
df_dummies = pd.get_dummies(df, columns=['boro']
```

	salary	vegan	boro_Bronx	boro_Brooklyn	boro_Manhattan	boro_Queens
0	103	No	0	0	1	0
1	89	No	0	0	0	1
2	142	No	0	0	1	0
3	54	Yes	0	1	0	0
4	63	Yes	0	1	0	0
5	219	No	1	0	0	0

```
df = pd.DataFrame({
  'boro': ['Brooklyn', 'Manhattan', 'Brooklyn',
           'Queens', 'Brooklyn', 'Staten Island'
      ],
  'salary': [61, 146, 142, 212, 98, 47],
  'vegan': ['Yes', 'No','Yes','No', 'Yes', 'No'
      ]})
df_dummies = pd.get_dummies(df, columns=['boro'
      ])
```

	salary	vegan	boro_Brooklyn	boro_Manhattan	boro_Queens	boro_Staten Island
0	61	Yes	1	0	0	0
1	146	No	0	1	0	0
2	142	Yes	1	0	0	0
3	212	No	0	0	1	0
4	98	Yes	1	0	0	0
5	47	No	0	0	0	1

Pandas Categorical Columns

```
df = pd.DataFrame({
    'boro': ['Manhattan', 'Queens', 'Manhattan', 'Brooklyn', 'Brooklyn', 'Bronx'],
    'salary': [103, 89, 142, 54, 63, 219],
    'vegan': ['No', 'No','No','Yes', 'Yes', 'No']})

df['boro'] = pd.Categorical(df.boro,
                            categories=['Manhattan', 'Queens', 'Brooklyn',
                                        'Bronx', 'Staten Island'])
pd.get_dummies(df, columns=['boro'])
```

	salary	vegan	boro_Manhattan	boro_Queens	boro_Brooklyn	boro_Bronx	boro_Staten Island
0	103	No	1	0	0	0	0
1	89	No	0	1	0	0	0
2	142	No	1	0	0	0	0
3	54	Yes	0	0	1	0	0
4	63	Yes	0	0	1	0	0
5	219	No	0	0	0	1	0

OneHotEncoder

```
import pandas as pd
df = pd.DataFrame({'salary': [103, 89, 142, 54, 63, 219],
                   'boro': ['Manhattan', 'Queens', 'Manhattan',
                            'Brooklyn', 'Brooklyn', 'Bronx']})

ce = OneHotEncoder().fit(df)
ce.transform(df).toarray()
```

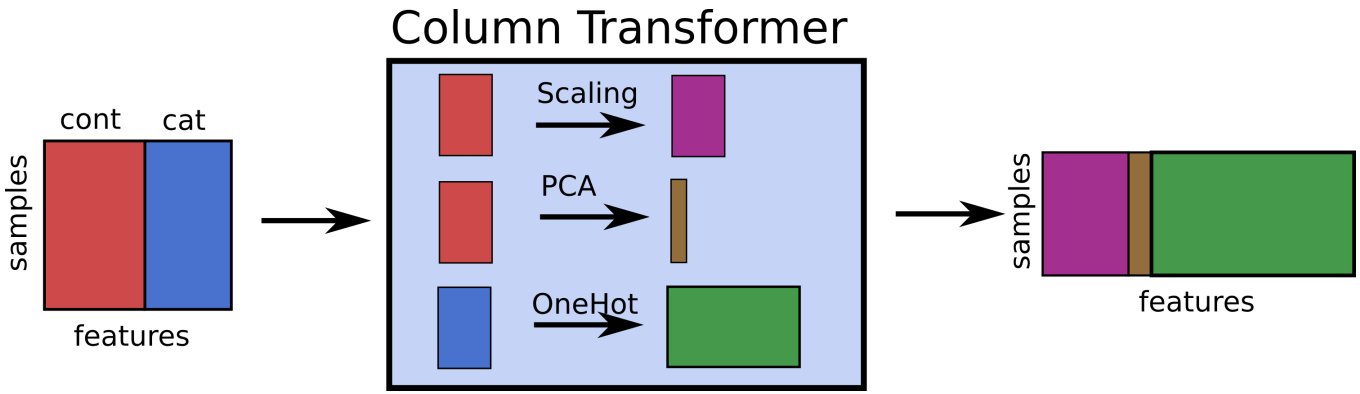
```
array([[ 0.,  0.,  1.,  0.,  0.,  0.,  0.,  1.,  0.,  0.],
       [ 0.,  0.,  0.,  1.,  0.,  0.,  1.,  0.,  0.,  0.],
       [ 0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,  1.,  0.],
       [ 0.,  1.,  0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.],
       [ 0.,  1.,  0.,  0.,  0.,  1.,  0.,  0.,  0.,  0.],
       [ 1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.]])
```

OneHotEncoder + ColumnTransformer

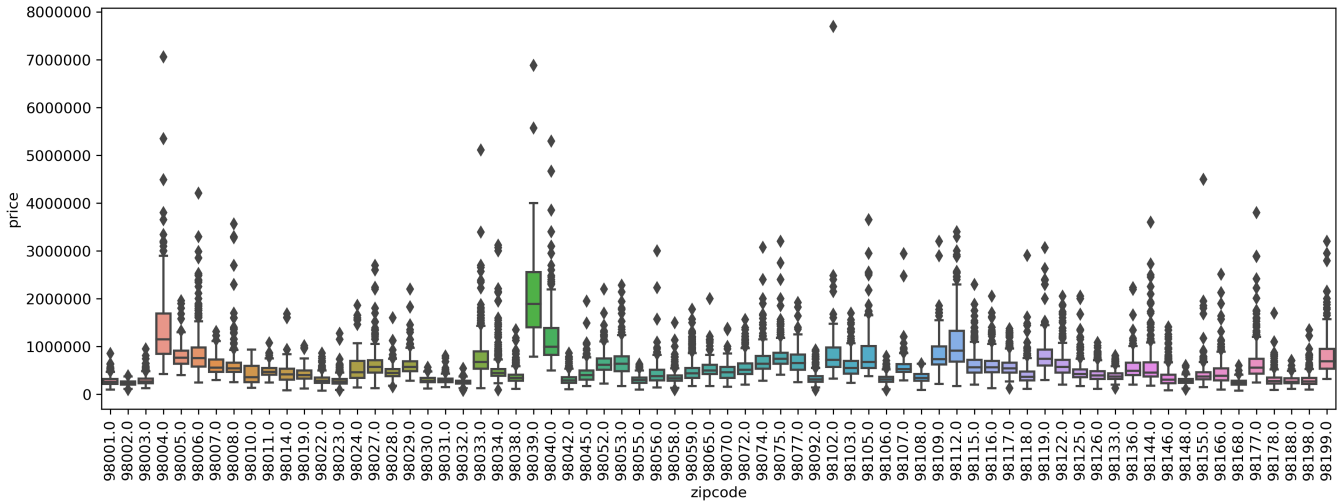
```
categorical = df.dtypes == object

preprocess = make_column_transformer(
    (StandardScaler(), ~categorical),
    (OneHotEncoder(), categorical))

model = make_pipeline(preprocess, LogisticRegression())
```



Target Encoding



- For high cardinality categorical features
- Instead of 70 one-hot variables, one "response encoded" variable.
- For regression- "average price in zip code"
- Binary classification– "building in this zip code have a likelihood p for class 1"
- Multiclass– One feature per class: probability distribution

Load Data, Include ZipCode

```
data = pd.read_csv("kc_house_data.csv", index_col=0)
X = data.frame.drop(['date', 'price'], axis=1)
X_train, X_test, y_train, y_test = train_test_split(X, target)
X_train.columns
```

```
Index(['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode', 'lat',
       'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

Explore House Data Set

```
1 X_train.head()
```

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	...	zipcode	lat	long	sqft_living15	sqft_lot15
10666	4.0	2.50	2160.0	7000.0	2.0	...	98029.0	47.566	-122.013	2300.0	7440.0
19108	4.0	4.25	3250.0	11780.0	2.0	...	98004.0	47.632	-122.203	1800.0	9000.0
20132	3.0	2.50	1280.0	1920.0	3.0	...	98105.0	47.662	-122.324	1450.0	1900.0
16169	4.0	1.50	1220.0	9600.0	1.0	...	98014.0	47.646	-121.909	1180.0	9000.0
16890	3.0	1.50	2120.0	6290.0	1.0	...	98108.0	47.566	-122.318	1620.0	5400.0

```
1 te = TargetEncoder(cols='zipcode').fit(X_train, y_train)
2 te.transform(X_train).head()
```

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	...	zipcode	lat	long	sqft_living15	sqft_lot15
10666	4.0	2.50	2160.0	7000.0	2.0	...	6.164e5	47.566	-122.013	2300.0	7440.0
19108	4.0	4.25	3250.0	11780.0	2.0	...	1.357e7	47.632	-122.203	1800.0	9000.0
20132	3.0	2.50	1280.0	1920.0	3.0	...	8.503e7	47.662	-122.324	1450.0	1900.0
16169	4.0	1.50	1220.0	9600.0	1.0	...	4.464e8	47.646	-121.909	1180.0	9000.0
16890	3.0	1.50	2120.0	6290.0	1.0	...	3.604e9	47.566	-122.318	1620.0	5400.0

```
1 y_train.groupby(X_train.zipcode).mean()[X_train.head().zipcode])
```

zipcode	98029.0	98004.0	98105.0	98014.0	98108.0
price	616356.941	1.357e6	850306.816	446448.065	360416.811

Explore House Data Set

```
X = data.frame.drop(['date', 'price', 'zipcode'], axis=1)
scores = cross_val_score(Ridge(), X, target)
np.mean(scores)
0.69
```

```
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import OneHotEncoder
X = data.frame.drop(['date', 'price'], axis=1)
ct = make_column_transformer((OneHotEncoder(), ['zipcode']), remainder='passthrough')
pipe_ohe = make_pipeline(ct, Ridge())
scores = cross_val_score(pipe_ohe, X, target)
np.mean(scores)
0.52
```

```
from category_encoders import TargetEncoder
X = data.frame.drop(['date', 'price'], axis=1)
pipe_target = make_pipeline(TargetEncoder(cols='zipcode'), Ridge())
scores = cross_val_score(pipe_target, X, target)
np.mean(scores)
0.78
```