task1

February 20, 2019

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1 Applied Machine Learning: Homework 2 - Task 1

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import warnings
        warnings.simplefilter('ignore')
```

We start by loading the data. We make sure to only treat missing values as NaN. Moreover, we also have to "force" some categorical features to be treated as such - some of them are treated as continuous because they contain numbers. Please note that most of the features listed as "discrete" by the description are kept as non-categorical features here: we only force those listed as "nominal" and "ordinal", and the discrete features that wouldn't make sense as continuous.

```
In [2]: #A list of the variables we want to "enforce" as categorical
        cat = ['MS SubClass', 'Overall Qual', 'Overall Cond', 'Mo Sold']
        catd = {}
        for e in cat:
            catd[e]='object'

        df = pd.read_excel("data/task1.xls", dtype=catd,
                           na_values=[''], keep_default_na=False)
```

The column 'MS SubClass' is, in a pretty straightforward way, a nominal variable in which the category names are number, so it needs to be forced as categorical.

The columns 'Overall Qual' and 'Overall Cond' actually pose a real problem. They are categorical, but ordered (ordinal), so keeping them as integers instead of objects would actually make sense, because we'd at least keep the order. Here, we completely lose it. However, we gain consistency in regards to other "ratings" columns such as 'Exter Qual' and 'Exter Cond' which are treated as unordered categoricals by pandas anyway. What we would really need to do is to take all the ordinal features and tell pandas the order for each one of them, but that would be too time-consuming.

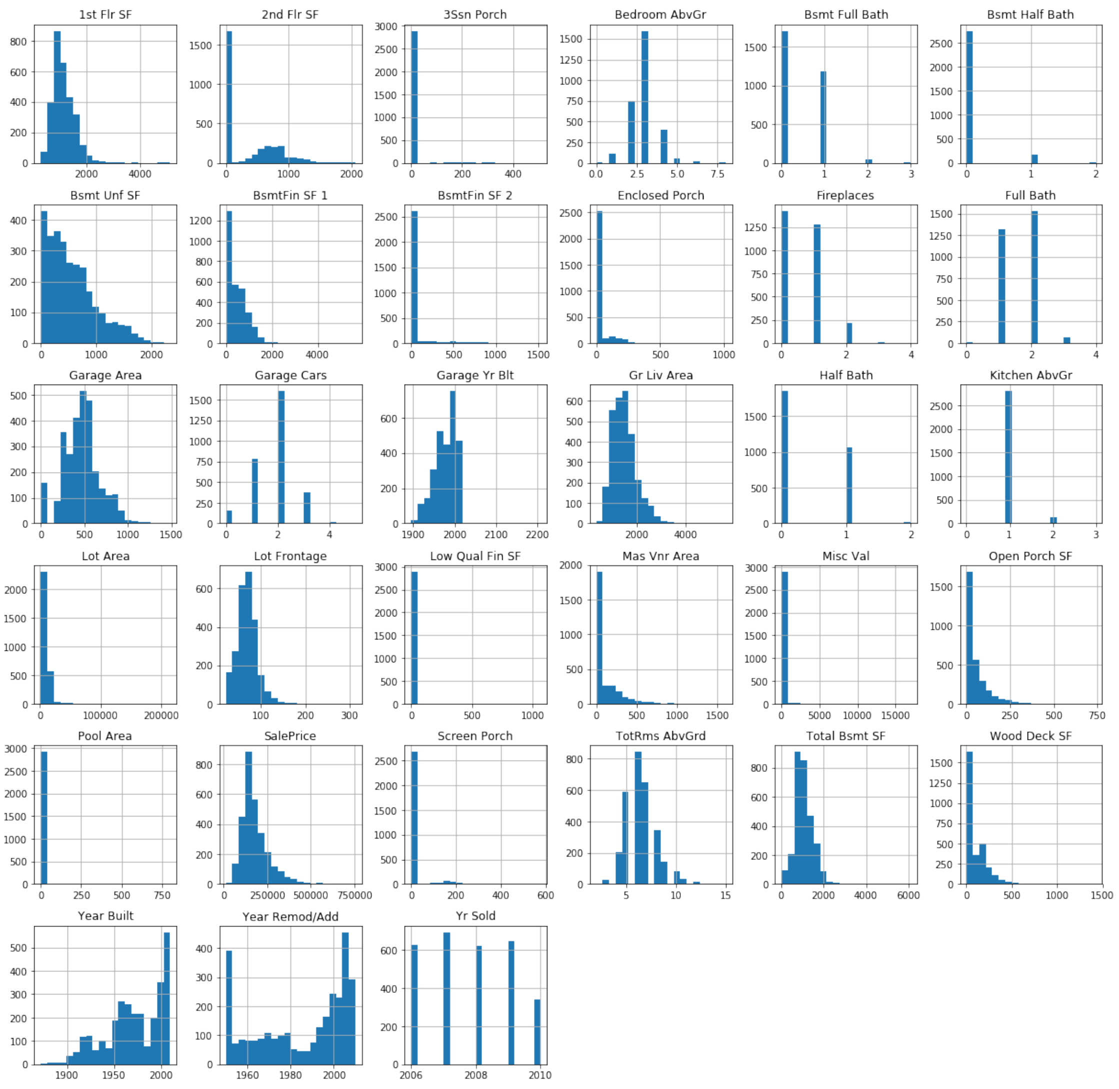
The column 'Mo Sold' corresponds to a "discrete" feature that wouldn't make sense as a continuous feature, because the ordering of the month doesn't matter. All the other discrete features (years, number of rooms...) are judged to make sense as a categorical because ordering matters in their case - and again, we don't want to spend all our time forcing a custom order on each of them.

We drop the "order" column, because we don't want it to have an influence in predictions. The pandas dataframe is already automatically indexed, so the column serves no purpose. For the same reasons, we drop the "PID" (parcel ID) feature, because it has no real use in prediction.

```
In [3]: df.drop(columns=['Order', 'PID'], inplace=True)
```

1.1

```
In [4]: _ = df.hist(figsize = (20, 20), bins=20)
```

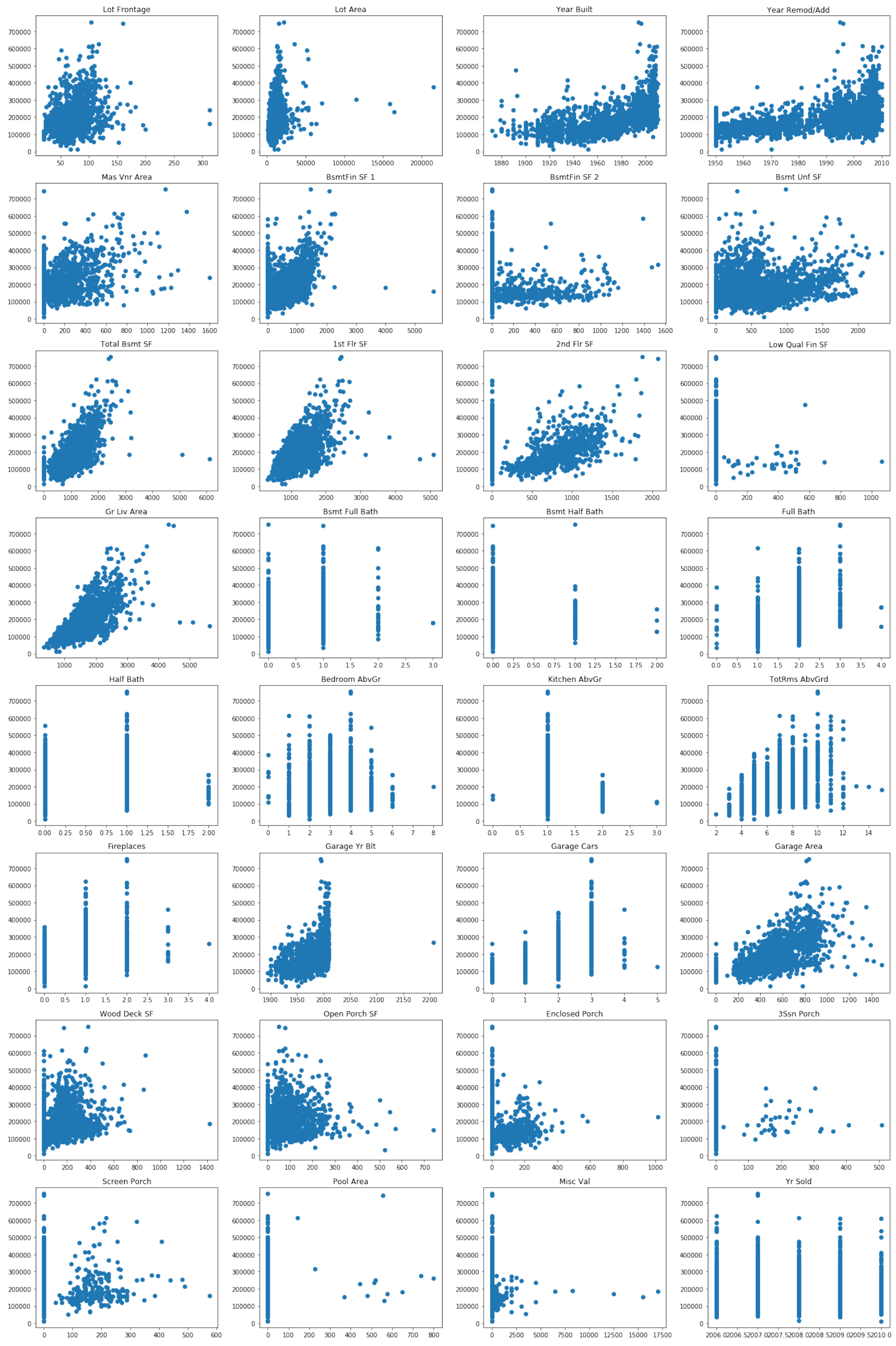


We notice that some histograms clearly show discrete variables, which we were expecting since we kept those as continuous when importing the data. More importantly, we can see that a lot of variables have a very high concentration of values near zero, which either indicates that there are some outliers that are "squeezing" the representation of the data into a single bin near zero, or that the data has a lot of missing values that are actually imputed as zero instead of missing or

NaN. This is probably the case in variables such as "2nd Flr SF" (second floor square feet) as not all houses have second floors: for those houses, instead of there being a missing value, the value is zero. In both cases (outliers and data inputed as 0), the data requires special treatment.

1.2

```
In [5]: fig, ax = plt.subplots(8, 4, figsize = (20, 30))
        # Columns with continuous features only
        cols_cont = df.columns[df.dtypes != object].tolist()
        for i in range(len(cols_cont)):
            if (cols_cont[i] != 'SalePrice'):
                ax[i//4][i % 4].scatter(df[cols_cont[i]], df['SalePrice'])
                ax[i//4][i % 4].set_title(cols_cont[i])
        plt.tight_layout()
```


Lot Frontage
Lot Area
Year Built
Year Remod/Add
Mas Vnr Area
BsmtFin SF 1
BsmtFin SF 2
Bsmt Unf SF
Total Bsmt SF
1st Flr SF
2nd Flr SF
Low Qual Fin SF
Gr Liv Area
Bsmt Full Bath
Bsmt Half Bath
Full Bath
Half Bath
Bedroom AbvGr
Kitchen AbvGr
TotRms AbvGrd
Fireplaces
Garage Yr Blt
Garage Cars
Garage Area
Wood Deck SF
Open Porch SF
Enclosed Porch
3Ssn Porch
Screen Porch
Pool Area
Misc Val
Yr Sold

Again, we see that some features are clearly discrete, which we again expected. Moreover, a lot of features (usually regarding parts of houses that aren't present in every house) show a vertical line on zero, meaning that a lot of values are imputed as zero. We also see some clear outliers such as the one in "Garage Yr Built" (year 2200). Finally, for some variables, we actually do see a pretty clear correlation with the sale price - most of them having to do with the house's surface area.

1.3

Let's first separate features and target.

```
In [6]: X = df.drop('SalePrice', axis=1)
        y = df['SalePrice']
```

Now, we do the train/test split

```
In [7]: from sklearn.model_selection import train_test_split
        X_train, X_test, y_train, y_test = train_test_split(X, y)
```

We also notice some missing values in some categorical variables. We assign the category 'missing' to those missing values.

```
In [8]: Xt_cols_cat = X_train.columns[X_train.dtypes == object].tolist()
        dict_missing = {i: 'Missing' for i in Xt_cols_cat}
        X_train.fillna(dict_missing, inplace=True)
```

```
In [9]: from sklearn.preprocessing import OneHotEncoder
        from sklearn.linear_model import LinearRegression
        lr = LinearRegression(fit_intercept=True)
        enc = OneHotEncoder(categories="auto")
        from sklearn.model_selection import cross_val_score
        R2s = []
        for i in Xt_cols_cat:
            Xtemp = enc.fit_transform(X_train[[i]])
            R2s.append(np.mean(cross_val_score(lr, Xtemp, y_train, cv=10)))
```

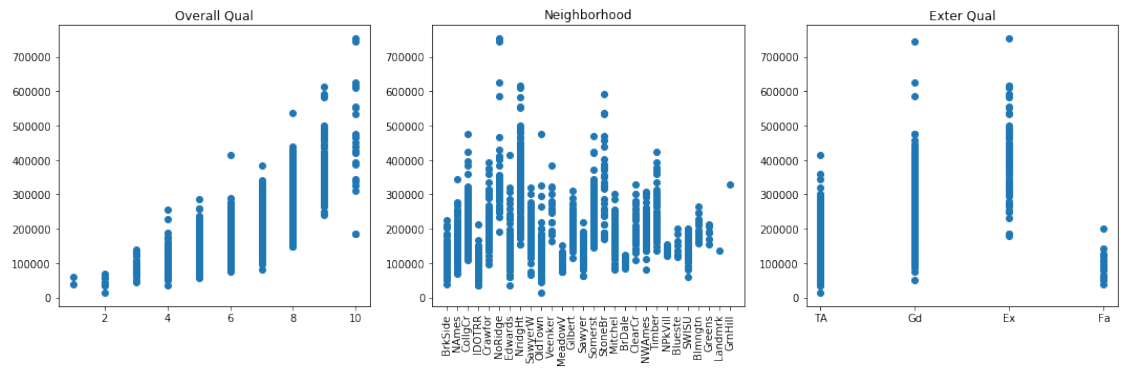
Here are the features with the best R^2 score:

```
In [10]: top3 = np.array(Xt_cols_cat)[np.array(R2s).argsort()[-3:][::-1]]
         top3.tolist()
```

```
Out[10]: ['Overall Qual', 'Neighborhood', 'Exter Qual']
```

And here is their relationship with the target:

```
In [11]: fig, ax = plt.subplots(1, 3, figsize = (15, 5))
         for i in range(3):
             ax[i].scatter(X_train[top3[i]], y_train)
             if i==1:
                 plt.sca(ax[1])
                 plt.xticks(rotation=90)
             ax[i].set_title(top3[i])
         plt.tight_layout()
```



1.4

```
In [12]: from sklearn.pipeline import Pipeline
         from sklearn.linear_model import Ridge, Lasso, ElasticNet
         from sklearn.preprocessing import StandardScaler
         from sklearn.impute import SimpleImputer
         from sklearn.compose import ColumnTransformer
```

Since we need to treat the missing values in the continuous variables, we add a "Simple Imputer" step to the pipelines.

```
In [13]: si = SimpleImputer(strategy="mean")
         ohe = OneHotEncoder(categories="auto", handle_unknown = 'ignore')
         lr = LinearRegression(fit_intercept=True)
         ridge = Ridge()
         lasso = Lasso(max_iter=5000)
         en = ElasticNet(max_iter=5000)
         Xt_cat = X_train.dtypes == object

         prep = ColumnTransformer([('imputer', si, ~Xt_cat), ("one-hot encoding", ohe, Xt_cat)]

         pipe_ols = Pipeline([('preprocessing', prep), ('lr', lr)])
         pipe_ridge = Pipeline([('preprocessing', prep), ('ridge', ridge)])
         pipe_lasso = Pipeline([('preprocessing', prep), ('lasso', lasso)])
         pipe_en = Pipeline([('preprocessing', prep), ('en', en)])

         s_ols = np.mean(cross_val_score(pipe_ols, X_train, y_train, cv=10))
         print("Score for OLS: " + str(s_ols))
         s_ridge = np.mean(cross_val_score(pipe_ridge, X_train, y_train, cv=10))
         print("Score for Ridge: " + str(s_ridge))

         s_lasso = np.mean(cross_val_score(pipe_lasso, X_train, y_train, cv=10))
         print("Score for Lasso: " + str(s_lasso))

         s_en = np.mean(cross_val_score(pipe_en, X_train, y_train, cv=10))
         print("Score for Elastic Net: " + str(s_en))
```

```
Score for OLS: 0.8696205060299432
Score for Ridge: 0.7086332361865224
Score for Lasso: 0.8730309801176089
Score for Elastic Net: 0.8437967476723912
```

Let's now try the same steps, but with an added Standard Scaler in the preprocessing.

```
In [14]: ssc = StandardScaler()
         pipe_pre_cont = Pipeline([('imputer', si), ('scaler', ssc)])
         #Making sure imputing is done before scaling
         prep = ColumnTransformer([('missing_scaling', pipe_pre_cont, ~Xt_cat),('one-hot encodi

         pipe_ols = Pipeline([('preprocessing', prep), ('lr', lr)])
         pipe_ridge = Pipeline([('preprocessing', prep), ('ridge', ridge)])
         pipe_lasso = Pipeline([('preprocessing', prep), ('lasso', lasso)])
         pipe_en = Pipeline([('preprocessing', prep), ('en', en)])

         s_ols = np.mean(cross_val_score(pipe_ols, X_train, y_train, cv=10))
         print("Score for OLS with Standard Scaling: " + str(s_ols))

         s_ridge = np.mean(cross_val_score(pipe_ridge, X_train, y_train, cv=10))
         print("Score for Ridge with Standard Scaling: " + str(s_ridge))

         s_lasso = np.mean(cross_val_score(pipe_lasso, X_train, y_train, cv=10))
         print("Score for Lasso with Standard Scaling: " + str(s_lasso))

         s_en = np.mean(cross_val_score(pipe_en, X_train, y_train, cv=10))
         print("Score for Elastic Net with Standard Scaling: " + str(s_en))
```

```
Score for OLS with Standard Scaling: 0.8723001923431036
Score for Ridge with Standard Scaling: 0.8778823231127323
Score for Lasso with Standard Scaling: 0.873023594099933
Score for Elastic Net with Standard Scaling: 0.8486953382888878
```

Scaling the data helps, especially with Ridge regression.

1.5

```
In [ ]: from sklearn.model_selection import GridSearchCV

        param_grid_r = {'ridge__alpha': np.logspace(-3, 3, 13)}
        param_grid_l = {'lasso__alpha': np.logspace(-3, 0, 13)}
        param_grid_en = {'en__alpha': np.logspace(-4, -1, 10),
                         'en__l1_ratio': [0.01, .1, .5, .9, .98, 1]}

        grid_r = GridSearchCV(pipe_ridge, param_grid_r, cv=10)
        _ = grid_r.fit(X_train, y_train)

        grid_l = GridSearchCV(pipe_lasso, param_grid_l, cv=10)
        _ = grid_l.fit(X_train, y_train)

        grid_en = GridSearchCV(pipe_en, param_grid_en, cv=10)
        _ = grid_en.fit(X_train, y_train)
```

```
In [ ]: s_ridge3 = grid_r.best_score_
        print("Score for Ridge with Standard Scaling and Grid Search CV: " + str(s_ridge3))

        s_lasso3 = grid_l.best_score_
        print("Score for Lasso with Standard Scaling and Grid Search CV: " + str(s_lasso3))

        s_en3 = grid_en.best_score_
        print("Score for Elastic Net with Standard Scaling and Grid Search CV: " + str(s_en3))
```

We see that the scores improve slightly for Ridge and Lasso regression. However, the increase for ElasticNet is much more visible, probably because we search across a 2D grid rather than 1D.

```
In [ ]: results_r = pd.DataFrame(grid_r.cv_results_)
        results_r.plot('param_ridge__alpha', 'mean_train_score')
        results_r.plot('param_ridge__alpha', 'mean_test_score', ax=plt.gca())
        plt.legend()
        plt.xscale("log")
        plt.xlabel("alpha")
        plt.title("Ridge Regression")
        plt.show()
```

```
In [ ]: results_l = pd.DataFrame(grid_l.cv_results_)
        results_l.plot('param_lasso__alpha', 'mean_train_score')
        results_l.plot('param_lasso__alpha', 'mean_test_score', ax=plt.gca())
        plt.legend()
        plt.xscale("log")
        plt.xlabel("alpha")
        plt.title("Lasso Regression")
        plt.show()
```

```
In [ ]: res = pd.pivot_table(pd.DataFrame(grid_en.cv_results_),
                             values='mean_test_score', index='param_en__alpha',
                             columns='param_en__l1_ratio')
        plt.figure(figsize = (10,7))
        plt.imshow(res)
        plt.colorbar()
        alphas = param_grid_en['en__alpha']
        l1_ratio = np.array(param_grid_en['en__l1_ratio'])
        plt.xlabel("l1_ratio")
        plt.ylabel("alpha")
        plt.yticks(range(len(alphas)), ["{:.4f}".format(a) for a in alphas])
        plt.xticks(range(len(l1_ratio)), l1_ratio);
```

1.6

We choose to display bar charts of the top 10 features for all 3 models - that is, the features with the largest coefficients in absolute value. We directly use the 'best estimator' attribute from the grid searches. Unfortunately, I haven't found a way to retrieve the corresponding feature names from the ColumnTransformer step of the pipeline. I can access the feature names returned by the 'one hot encoding' steps of the categorical preprocessing pipeline, but I can't access the feature names in the output of the column transformer itself (because it contains pipelines that don't support the get_feature_names() method).

```
In [ ]: coeffs_ridge = np.abs(grid_r.best_estimator_.named_steps['ridge'].coef_)
        top10_ridge = np.argsort(coeffs_ridge)[::-1][:10]
        plt.bar([str(i) for i in top10_ridge], coeffs_ridge[top10_ridge])
        plt.title("Ridge Top 10 coefficients")
        plt.show()
```

```
In [ ]: coeffs_lasso = np.abs(grid_l.best_estimator_.named_steps['lasso'].coef_)
        top10_lasso = np.argsort(coeffs_lasso)[::-1][:10]
        plt.bar([str(i) for i in top10_lasso], coeffs_lasso[top10_lasso])
        plt.title("Lasso Top 10 coefficients")
        plt.show()
```

```
In [ ]: coeffs_en = np.abs(grid_en.best_estimator_.named_steps['en'].coef_)
        top10_en = np.argsort(coeffs_en)[::-1][:10]
        plt.bar([str(i) for i in top10_en], coeffs_en[top10_en])
        plt.title("ElasticNet Top 10 coefficients")
        plt.show()
```

We can see that the models generally agree on which features are important: features number 311 and 122 are top 3 every time, generally followed by 312, 92 and 149. We would really like to know to which features that actually corresponds, but unfortunately we haven't found a way.

task2

February 20, 2019

Corentin Llorca (cl3783)

1 Applied Machine Learning: Homework 2 - Task 2

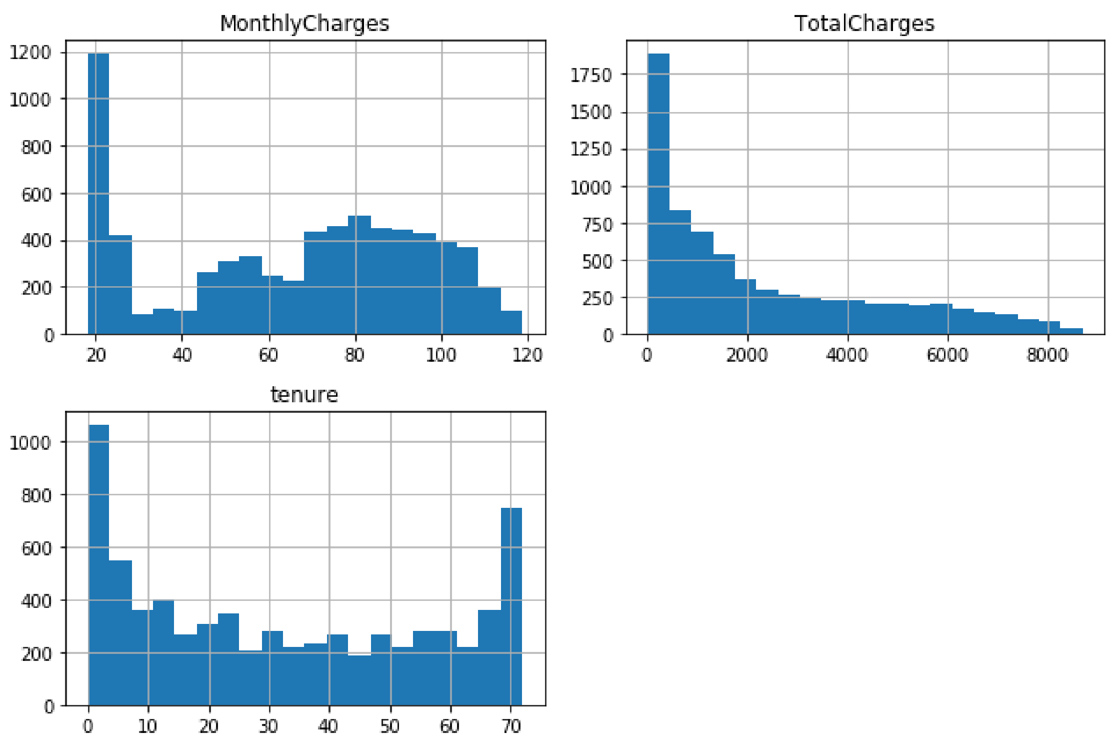
```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import warnings
        warnings.simplefilter('ignore')
```

We start by loading the data. The feature 'SeniorCitizen' will be read as a number by pandas, so we enforce it as categorical. We also notice that TotalCharges is read as an object, so we enforce it as a float.

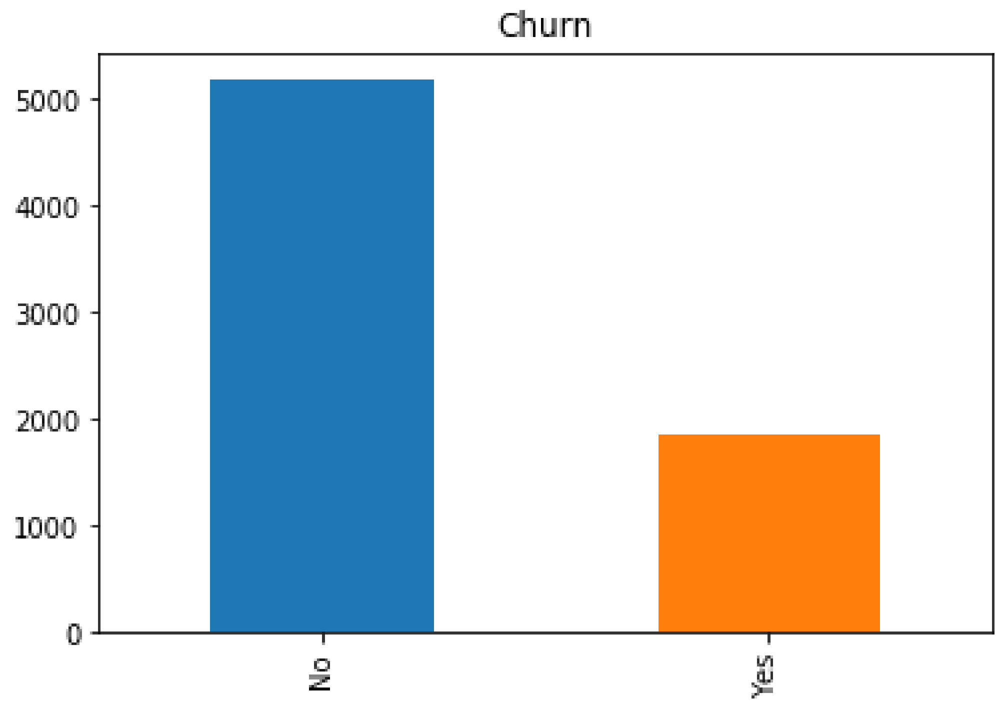
```
In [2]: df = pd.read_csv("data/task2.csv", dtype={'SeniorCitizen': object}, na_values=[' '])
```

2.1

```
In [3]: df.hist(figsize = (9,6), bins = 20)
        plt.tight_layout()
        plt.show()
```



```
In [4]: df['Churn'].value_counts().plot(kind='bar')
        plt.title('Churn')
        plt.show()
```



2.2

```
In [5]: df.drop('customerID', axis=1, inplace=True)
        X = df.drop('Churn', axis=1)
        y = df['Churn']
        from sklearn.model_selection import train_test_split
        X_train, X_test, y_train, y_test = train_test_split(X, y)

In [6]: from sklearn.linear_model import LogisticRegression
        from sklearn.neighbors import NearestCentroid
        from sklearn.svm import LinearSVC
        from sklearn.pipeline import Pipeline
        from sklearn.compose import ColumnTransformer
        from sklearn.preprocessing import StandardScaler, OneHotEncoder
        from sklearn.impute import SimpleImputer
        from sklearn.model_selection import cross_val_score

In [7]: si = SimpleImputer(strategy="mean")
        ohe = OneHotEncoder(categories="auto", handle_unknown = 'ignore')
        logr = LogisticRegression()
        nc = NearestCentroid()
        lsvc = LinearSVC()

        Xt_cat = X_train.dtypes == object
        pipe_prep_cont = Pipeline([('imputer', si)])
        pipe_prep_cat = Pipeline([('ohe', ohe)])

        prep = ColumnTransformer([('continuous', pipe_prep_cont, ~Xt_cat),('categorical', pipe_

        pipe_logr = Pipeline([('preprocessing', prep), ('logr', logr)])
        pipe_nc = Pipeline([('preprocessing', prep), ('nc', nc)])
        pipe_lsvc = Pipeline([('preprocessing', prep), ('lsvc', lsvc)])

        s_logr = np.mean(cross_val_score(pipe_logr, X_train, y_train, cv=10))
        print("Score for Logistic Regression: " + str(s_logr))

        s_nc = np.mean(cross_val_score(pipe_nc, X_train, y_train, cv=10))
        print("Score for Nearest Centroid: " + str(s_nc))

        s_lsvc = np.mean(cross_val_score(pipe_lsvc, X_train, y_train, cv=10))
        print("Score for Linear SVC: " + str(s_lsvc))
```

```
Score for Logistic Regression: 0.7962957476755843
Score for Nearest Centroid: 0.5187528865994284
Score for Linear SVC: 0.7001111860490169
```

The results vary a lot between the different classifiers. Logistic regression works the best, then Linear SVC, and Nearest Centroid performs very poorly. Let's now try with scaling the data.

```
In [8]: ssc = StandardScaler()
        pipe_prep_cont = Pipeline([('imputer', si), ('scaler', ssc)])
        prep = ColumnTransformer([('continuous', pipe_prep_cont, ~Xt_cat),('categorical', pipe_

        pipe_logr = Pipeline([('preprocessing', prep), ('logr', logr)])
        pipe_nc = Pipeline([('preprocessing', prep), ('nc', nc)])
        pipe_lsvc = Pipeline([('preprocessing', prep), ('lsvc', lsvc)])

        s_logr = np.mean(cross_val_score(pipe_logr, X_train, y_train, cv=10))
        print("Score for Logistic Regression with standard scaler: " + str(s_logr))

        s_nc = np.mean(cross_val_score(pipe_nc, X_train, y_train, cv=10))
        print("Score for Nearest Centroid with standard scaler: " + str(s_nc))

        s_lsvc = np.mean(cross_val_score(pipe_lsvc, X_train, y_train, cv=10))
        print("Score for Linear SVC with standard scaler: " + str(s_lsvc))
```

```
Score for Logistic Regression with standard scaler: 0.7970536814557299
Score for Nearest Centroid with standard scaler: 0.7334444922079615
Score for Linear SVC with standard scaler: 0.7976225806777706
```

Scaling the data actually significantly improves both Nearest Centroid and SVM. With scaling, Nearest Centroid still performs the worst but linear SVC and Logistic Regression are roughly equivalent.

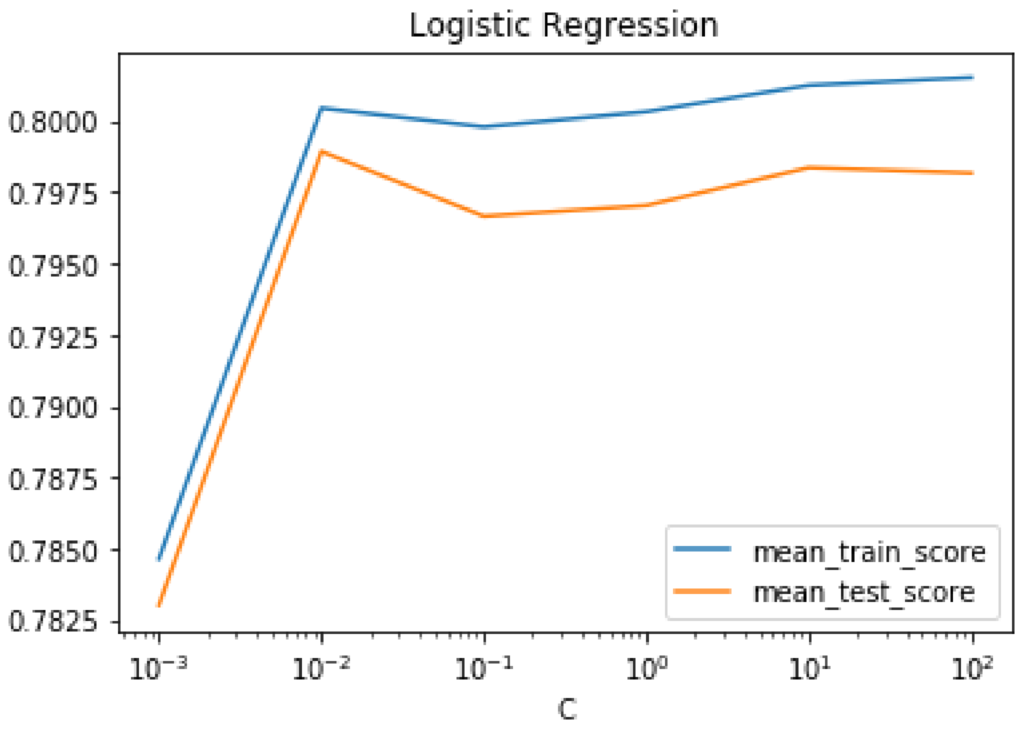
2.3

```
In [9]: from sklearn.model_selection import GridSearchCV

        param_grid_logr = {'logr__C': np.logspace(-3, 2, 6)}
        param_grid_nc = {'nc__shrink_threshold': np.linspace(0, 2, 20)}
        param_grid_lsvc = {'lsvc__C': np.logspace(-3, 2, 6)}

        grid_logr = GridSearchCV(pipe_logr, param_grid_logr, cv=10)
        _ = grid_logr.fit(X_train, y_train)

        grid_nc = GridSearchCV(pipe_nc, param_grid_nc, cv=10)
        _ = grid_nc.fit(X_train, y_train)

        grid_lsvc = GridSearchCV(pipe_lsvc, param_grid_lsvc, cv=10)
        _ = grid_lsvc.fit(X_train, y_train)

        s_logr = grid_logr.best_score_
        print("Score for Logistic Regression with Standard Scaling and Grid Search CV: " + str
        s_nc = grid_nc.best_score_
        print("Score for Nearest Centroids with Standard Scaling and Grid Search CV: " + str(s_

        s_lsvc = grid_lsvc.best_score_
        print("Score for Linear SVC with Standard Scaling and Grid Search CV: " + str(s_lsvc))
```

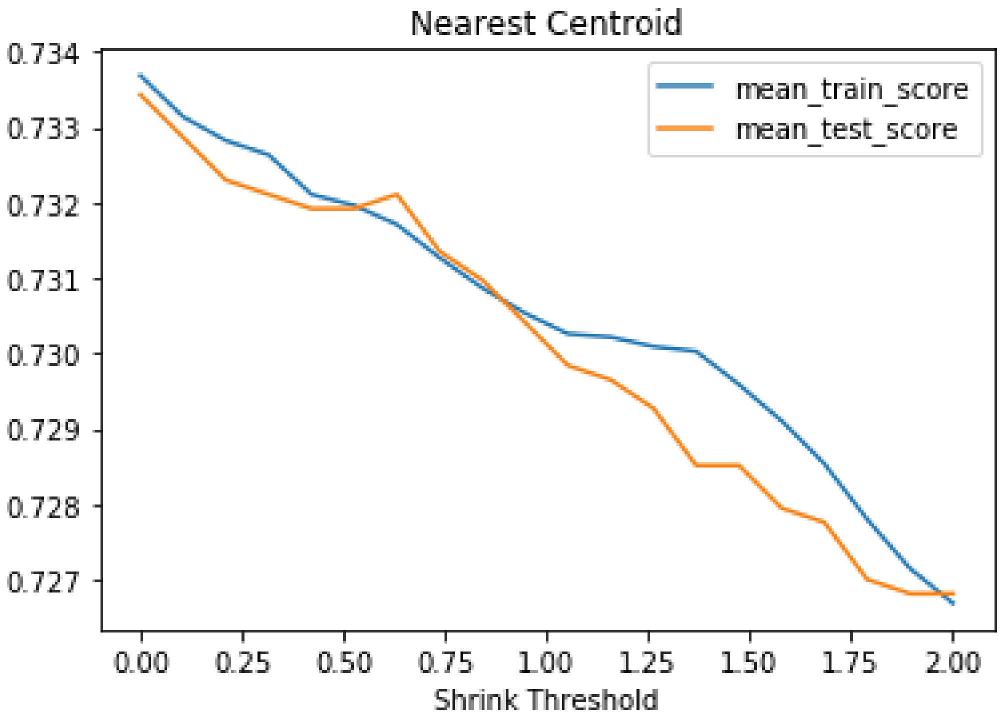
```
Score for Logistic Regression with Standard Scaling and Grid Search CV: 0.7989397955319955
Score for Nearest Centroids with Standard Scaling and Grid Search CV: 0.733434305187429
Score for Linear SVC with Standard Scaling and Grid Search CV: 0.798750473305566
```

The results barely improve with GridSearch. It looks like the default parameters give us good enough models.

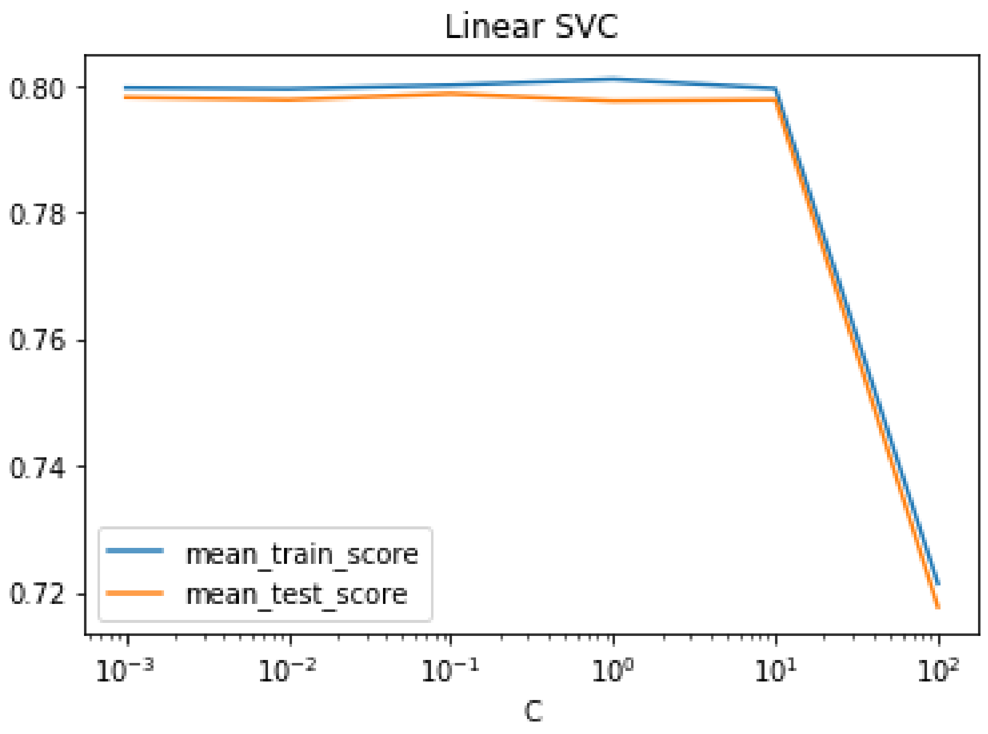
```
In [10]: results_logr = pd.DataFrame(grid_logr.cv_results_)
         results_logr.plot('param_logr__C', 'mean_train_score')
         results_logr.plot('param_logr__C', 'mean_test_score', ax=plt.gca())
         plt.legend()
         plt.xscale("log")
         plt.xlabel("C")
         plt.title("Logistic Regression")
         plt.show()
```



```
In [11]: results_nc = pd.DataFrame(grid_nc.cv_results_)
         results_nc.plot('param_nc__shrink_threshold', 'mean_train_score')
         results_nc.plot('param_nc__shrink_threshold', 'mean_test_score', ax=plt.gca())
         plt.legend()
         plt.xlabel("Shrink Threshold")
         plt.title("Nearest Centroid")
         plt.show()
```



```
In [12]: results_lsvc = pd.DataFrame(grid_lsvc.cv_results_)
         results_lsvc.plot('param_lsvc__C', 'mean_train_score')
         results_lsvc.plot('param_lsvc__C', 'mean_test_score', ax=plt.gca())
         plt.legend()
         plt.xscale("log")
         plt.xlabel("C")
         plt.title("Linear SVC")
         plt.show()
```



2.4

Let's first view the parameters currently found by GridSearchCV:

```
In [13]: bp_logr = grid_logr.best_params_
         print("Best parameters for Logistic Regression: " + str(bp_logr))

         bp_nc = grid_nc.best_params_
         print("Best parameters for Nearest Centroids: " + str(bp_nc))

         bp_lsvc = grid_lsvc.best_params_
         print("Best parameters for Linear SVC: " + str(bp_lsvc))
```

```
Best parameters for Logistic Regression: {'logr__C': 0.01}
Best parameters for Nearest Centroids: {'nc__shrink_threshold': 0.0}
Best parameters for Linear SVC: {'lsvc__C': 0.1}
```

Let's now find them again using a k-fold with shuffling cross-validation.

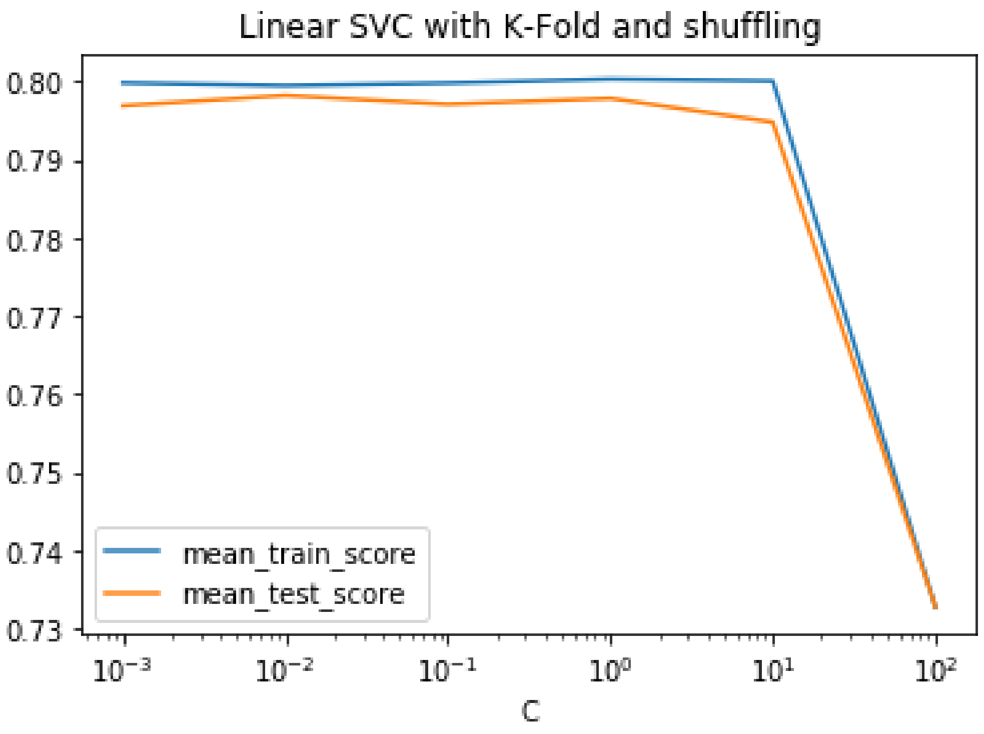
```
In [14]: from sklearn.model_selection import KFold

         cvs=KFold(n_splits=10, shuffle=True)
```

```
grid_logr = GridSearchCV(pipe_logr, param_grid_logr, cv=cvs)
_ = grid_logr.fit(X_train, y_train)

grid_nc = GridSearchCV(pipe_nc, param_grid_nc, cv=cvs)
_ = grid_nc.fit(X_train, y_train)

grid_lsvc = GridSearchCV(pipe_lsvc, param_grid_lsvc, cv=cvs)
_ = grid_lsvc.fit(X_train, y_train)

bp_logr = grid_logr.best_params_
print("Best parameters for Logistic Regression with k-fold shuffling CV: " + str(bp_lo

bp_nc = grid_nc.best_params_
print("Best parameters for Nearest Centroids with k-fold shuffling CV: " + str(bp_nc)

bp_lsvc = grid_lsvc.best_params_
print("Best parameters for Linear SVC with k-fold shuffling CV: " + str(bp_lsvc))
```

```
Best parameters for Logistic Regression with k-fold shuffling CV: {'logr__C': 0.01}
Best parameters for Nearest Centroids with k-fold shuffling CV: {'nc__shrink_threshold': 0.0}
Best parameters for Linear SVC with k-fold shuffling CV: {'lsvc__C': 0.01}
```

We can see that the parameters don't change, except for Linear SVC where the best C is now 0.001 instead of 1. However, let's view the corresponding plot:

```
In [15]: results_lsvc = pd.DataFrame(grid_lsvc.cv_results_)
         results_lsvc.plot('param_lsvc__C', 'mean_train_score')
         results_lsvc.plot('param_lsvc__C', 'mean_test_score', ax=plt.gca())
         plt.legend()
         plt.xscale("log")
         plt.xlabel("C")
         plt.title("Linear SVC with K-Fold and shuffling")
         plt.show()
```



We can see that the difference between 0.001 and 1 is very minimal in terms of performance - as it was in the previous plot. So the change in best parameter isn't really significant.

Let's now add a random state to our K-Fold.

```
In [16]: cvs=KFold(n_splits=10, shuffle=True, random_state=1)

         grid_logr = GridSearchCV(pipe_logr, param_grid_logr, cv=cvs)
         _ = grid_logr.fit(X_train, y_train)

         grid_nc = GridSearchCV(pipe_nc, param_grid_nc, cv=cvs)
         _ = grid_nc.fit(X_train, y_train)

         grid_lsvc = GridSearchCV(pipe_lsvc, param_grid_lsvc, cv=cvs)
         _ = grid_lsvc.fit(X_train, y_train)

         bp_logr = grid_logr.best_params_
         print("Best parameters for Logistic Regression with k-fold shuffling CV and random sta
               + str(bp_logr))

         bp_nc = grid_nc.best_params_
         print("Best parameters for Nearest Centroids with k-fold shuffling CV and random state
               + str(bp_nc))

         bp_lsvc = grid_lsvc.best_params_
```

```
        print("Best parameters for Linear SVC with k-fold shuffling CV and random state on CV
              + str(bp_lsvc))
```

```
Best parameters for Logistic Regression with k-fold shuffling CV and random state on CV: {'logr
Best parameters for Nearest Centroids with k-fold shuffling CV and random state on CV: {'nc__sh
Best parameters for Linear SVC with k-fold shuffling CV and random state on CV: {'lsvc__C': 0.
```

The scores don't change at all from last time - which is reassuring since it means our models are not heavily affected by randomness.

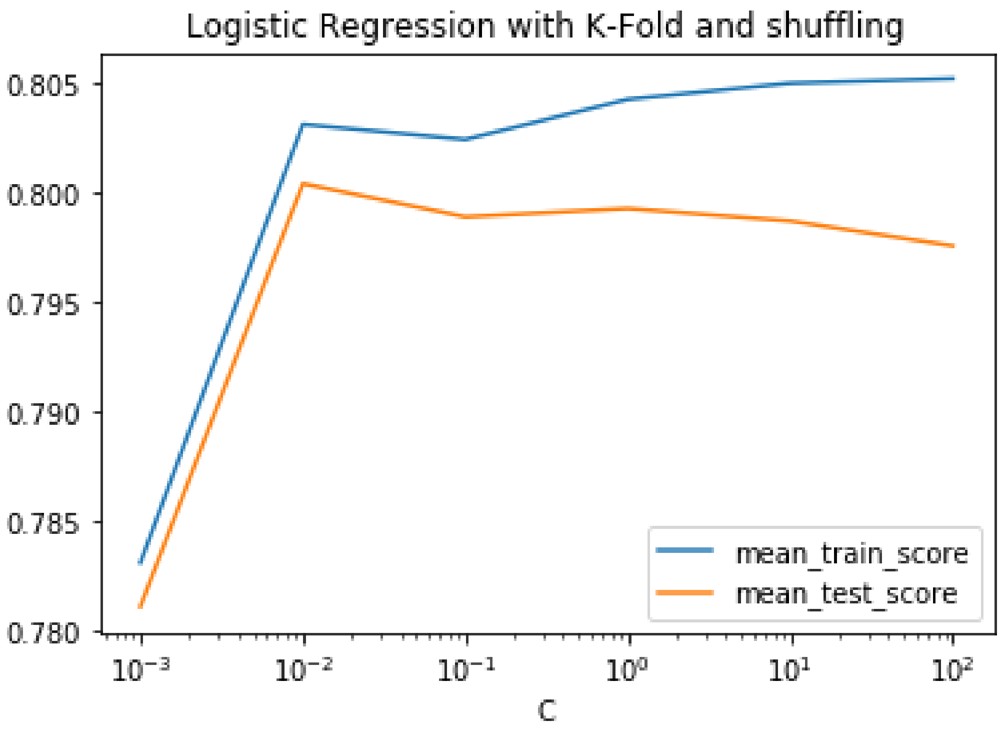
Finally, let's also add a random state for the splitting of the data between train set and test set.

```
In [17]: X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)
         grid_logr = GridSearchCV(pipe_logr, param_grid_logr, cv=cvs)
         _ = grid_logr.fit(X_train, y_train)

         grid_nc = GridSearchCV(pipe_nc, param_grid_nc, cv=cvs)
         _ = grid_nc.fit(X_train, y_train)

         grid_lsvc = GridSearchCV(pipe_lsvc, param_grid_lsvc, cv=cvs)
         _ = grid_lsvc.fit(X_train, y_train)

         bp_logr = grid_logr.best_params_
         print("Best parameters for Logistic Regression with k-fold shuffling CV and random sta
               + str(bp_logr))

         bp_nc = grid_nc.best_params_
         print("Best parameters for Nearest Centroids with k-fold shuffling CV and random state
               + str(bp_nc))

         bp_lsvc = grid_lsvc.best_params_
         print("Best parameters for Linear SVC with k-fold shuffling CV and random state on CV
               + str(bp_lsvc))
```

```
Best parameters for Logistic Regression with k-fold shuffling CV and random state on CV and tra
 {'logr__C': 0.01}
Best parameters for Nearest Centroids with k-fold shuffling CV and random state on CV and train
 {'nc__shrink_threshold': 0.0}
Best parameters for Linear SVC with k-fold shuffling CV and random state on CV and train/test s
 {'lsvc__C': 0.001}
```

This time, the best C parameter for Logistic Regression changes from 1 to 0.01. But again, let's plot the evolution of the scores according to that parameter:

```
In [18]: results_logr = pd.DataFrame(grid_logr.cv_results_)
         results_logr.plot('param_logr__C', 'mean_train_score')
         results_logr.plot('param_logr__C', 'mean_test_score', ax=plt.gca())
         plt.legend()
         plt.xscale("log")
         plt.xlabel("C")
         plt.title("Logistic Regression with K-Fold and shuffling")
         plt.show()
```

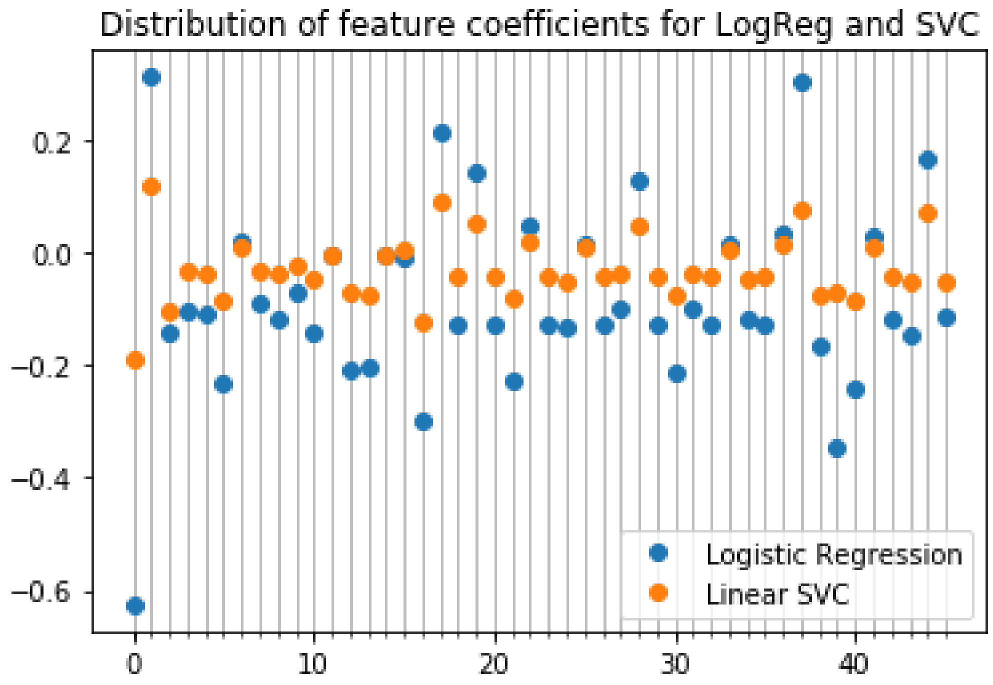


Again, we can see that the curve is rougly constant from 0.01 on, so it's not really a surprise that a slight change (e.g. changing the train-test split) would affect the maximum of the curve, since it's always going to be on that straight line between 0.01 and 100.

2.5

We display a 'dot plot' of feature coefficients for both models.

```
In [19]: coeffs_logr = grid_logr.best_estimator_.named_steps['logr'].coef_
         coeffs_lsvc = grid_lsvc.best_estimator_.named_steps['lsvc'].coef_
         plt.plot(coeffs_logr[0], 'o', label='Logistic Regression')
         plt.plot(coeffs_lsvc[0], 'o', label='Linear SVC')
         plt.legend()
         ax = plt.gca()
         ax.set_xticks(range(len(coeffs_logr[0])), minor=True)
         plt.gca().xaxis.grid(True, which='minor')
         plt.title("Distribution of feature coefficients for LogReg and SVC")
         plt.show()
```



We can wee that the general distribution of the feature coefficients is roughly similar between the two models (in particular, features 1, 17, 19, 37 and 44 are important in both), even though the amplitude of the coefficients is generally larger in Logistic Regression.