Machine Learning Project

March 27, 2022

[1]:
```
# %config Completer.use_jedi = False  # enable code auto-completion
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import HuberRegressor, Ridge, LogisticRegression
from sklearn.model_selection import train_test_split, KFold
from sklearn.svm import SVC
from sklearn.metrics import mean_squared_error, accuracy_score, r2_score    #␣
 ↪function to calculate mean squared error
```

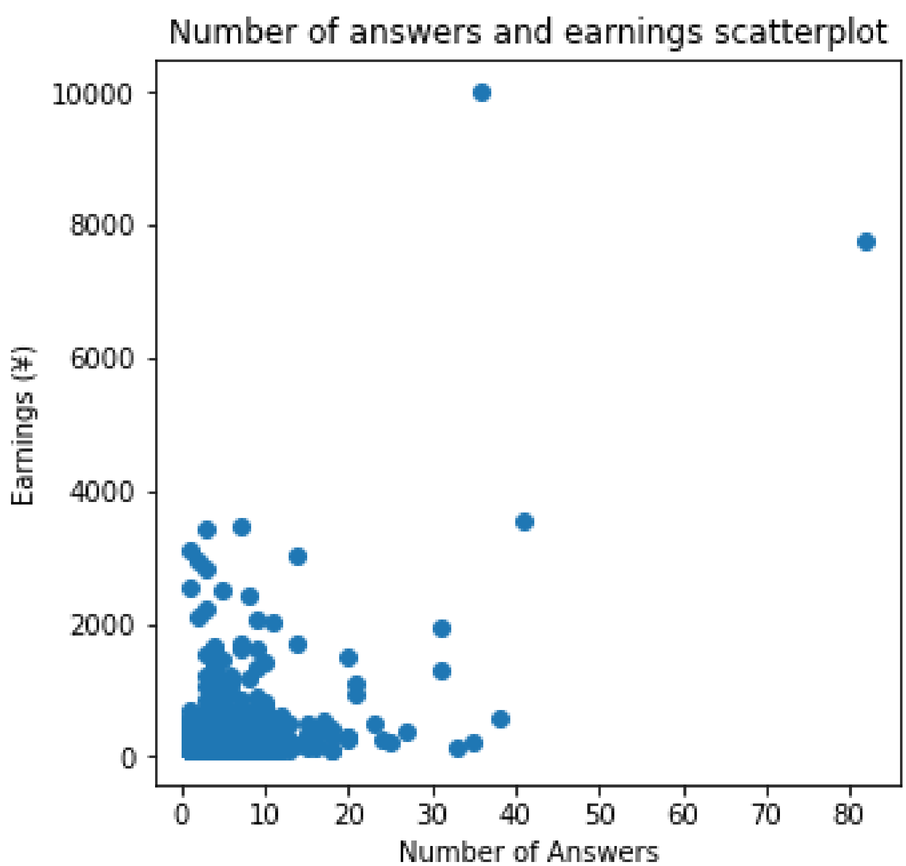
[2]:
```
df = pd.read_excel("earnings.xlsx")
print(df)
```

```
     Answers   Views                    Topic  External Traffic Percentage  \
0         36  247835            Social / News                            3
1         82  332393        Health / Psychology                          2
2         41  455160            Social / News                           19
3          7  106588        Culture / Politics                           2
4          3   65732            Social / News                            1
..       …       …                      …                          …
495        1    1134        Culture / Politics                          81
496        3    1339       Education / Science                          93
497        5    3159  Entertainment / Hobbies                          22
498       11    4139       Love / Relationship                           4
499        6    1068             Life / Habit                          94

     Earnings                                   Question details
0       10005  What's wrong with customs? You can play with y…
1        7785  It's very unpleasant to see someone eating out…
2        3542  I'm wondering if I should get the corona vacci…
3        3462  Why didn't the United States make Japan a poor…
4        3445  Do you think NASA has top secret files that ca…
..        …                                                …
495        83  What do the Chinese think about the Tank Man i…
496        83  What happens when citric acid and carbonated w…
497        82              What are your favorite top 10 movies?
498        82                 Can you buy your heart with money?
499        82  What is the temperature of the air conditioner…
```

[500 rows x 6 columns]

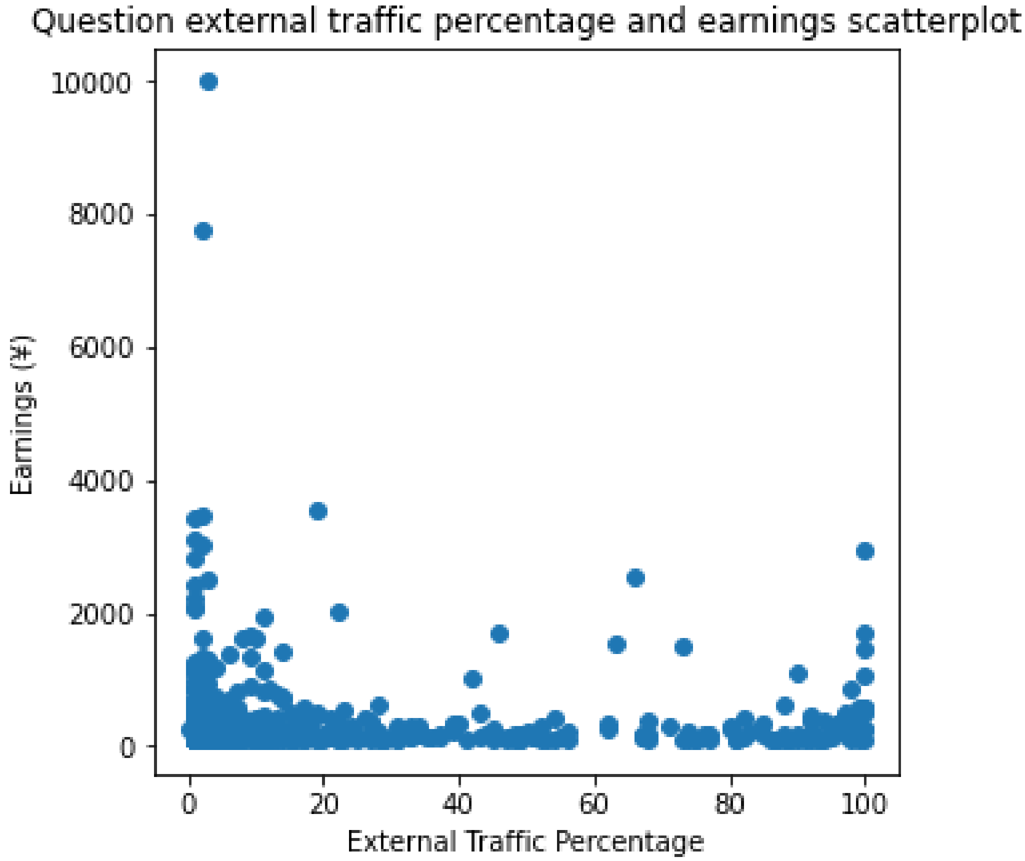
[3]:
```
external_traffic_percentage = df["External Traffic Percentage"].to_numpy()
topics = df["Topic"].to_numpy()
answers = df["Answers"].to_numpy()
views = df["Views"].to_numpy()
earnings = df["Earnings"].to_numpy()
```

[4]:
```
fig, axes = plt.subplots(figsize=(5,5))
axes.scatter(answers, earnings);
axes.set_xlabel("Number of Answers")
axes.set_ylabel("Earnings (¥)")
axes.set_title("Number of answers and earnings scatterplot")
plt.show()
```

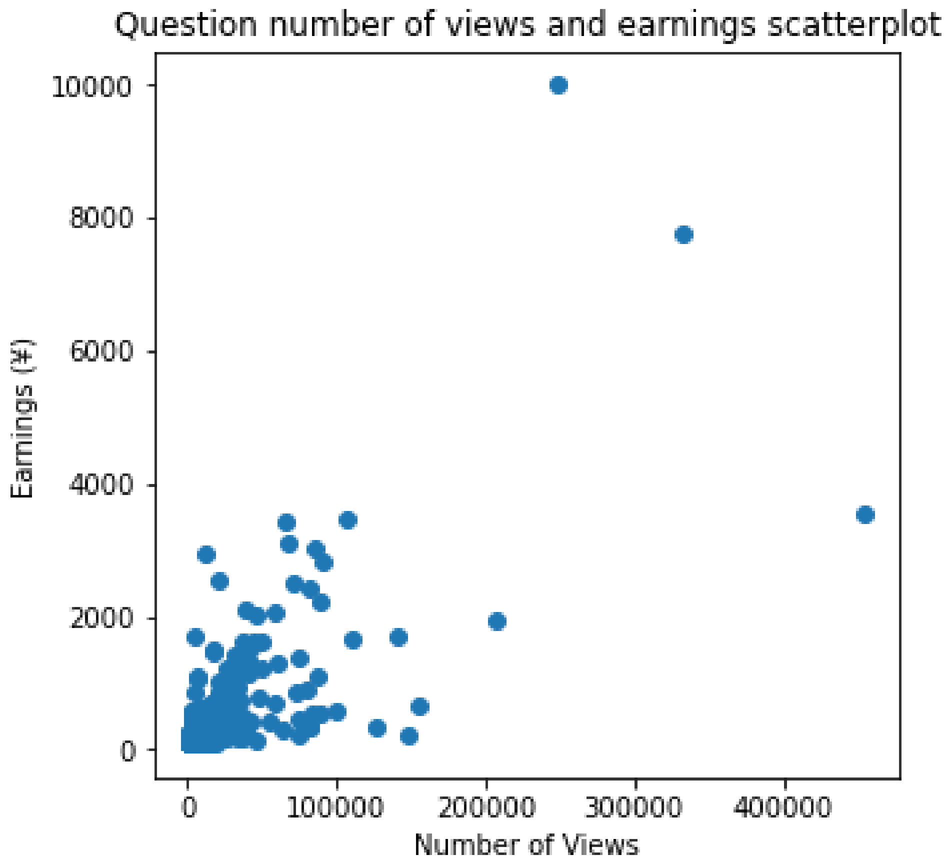


[5]:
```
fig, axes = plt.subplots(figsize=(5,5))
axes.scatter(external_traffic_percentage, earnings);
axes.set_xlabel("External Traffic Percentage")
axes.set_ylabel("Earnings (¥)")
```

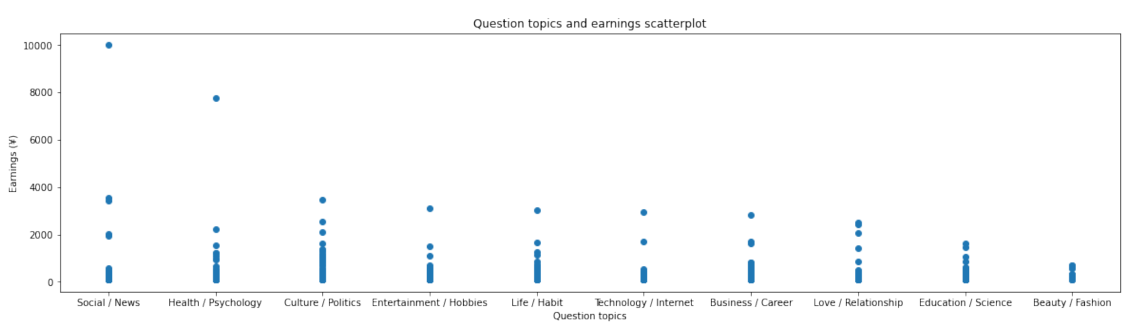
```
axes.set_title("Question external traffic percentage and earnings scatterplot")
plt.show()
```



[6]:
```
fig, axes = plt.subplots(figsize=(5,5))
axes.scatter(views, earnings);
axes.set_xlabel("Number of Views")
axes.set_ylabel("Earnings (¥)")
axes.set_title("Question number of views and earnings scatterplot")
plt.show()
```



[7]:
```
fig, axes = plt.subplots(1, 1, figsize=(20,5))
axes.scatter(topics, earnings);
axes.set_xlabel("Question topics")
axes.set_ylabel("Earnings (¥)")
axes.set_title("Question topics and earnings scatterplot")
plt.show()
```



[8]:
```
# Huber Regression, Ridge Regression model comparison function

def model_comparison(X, y, feature):
    tr_error = { "Huber": [], "Ridge": [] }
    val_error = { "Huber": [], "Ridge": [] }
    slope = { "Huber": [], "Ridge": [] }
    intercept = { "Huber": [], "Ridge": [] }
    predictors = { "Huber": [], "Ridge": [] }

    # In the first step we will split the data in testing and remaining dataset
    X_rem, X_test, y_rem, y_test = train_test_split(X, y, train_size=0.90,␣
↪random_state = 42)

    fig, axes = plt.subplots(5, 1, figsize=(5,25))

    K = 5  # Number of splits
    kf = KFold(n_splits=K, shuffle=True, random_state=42)    # Create a KFold␣
↪object with 'K' splits
    i = 0
    for train_indices, val_indices in kf.split(X_rem):
        X_train = X_rem[train_indices,:]    # Get the training set
        X_val = X_rem[val_indices,:]    # Get the validation set
        y_train = y_rem[train_indices]    # Get the training set
        y_val = y_rem[val_indices]    # Get the validation set

        # for Huber Regression model training
        HuberModel = HuberRegressor(epsilon = 1)
        fitHuberModel = HuberModel.fit(X_train, y_train)
        predictors["Huber"].append(fitHuberModel)
        slope["Huber"].append(fitHuberModel.coef_[0])
        intercept["Huber"].append(fitHuberModel.intercept_)
        y_pred_train_Huber = fitHuberModel.predict(X_train)
        # for Huber Regression validation
        y_pred_val_Huber = fitHuberModel.predict(X_val)
        tr_error["Huber"].append(mean_squared_error(y_train,␣
↪y_pred_train_Huber))
        val_error["Huber"].append(mean_squared_error(y_val, y_pred_val_Huber))

        # for Ridge Regression model training
        RidgeModel = Ridge(alpha=1, solver='svd')
        fitRidgeModel = RidgeModel.fit(X_train, y_train)
        predictors["Ridge"].append(fitRidgeModel)
        slope["Ridge"].append(fitRidgeModel.coef_[0])
        intercept["Ridge"].append(fitRidgeModel.intercept_)
        y_pred_train_Ridge = fitRidgeModel.predict(X_train)
        # for Ridge Regression validation
        y_pred_val_Ridge = fitRidgeModel.predict(X_val)
```

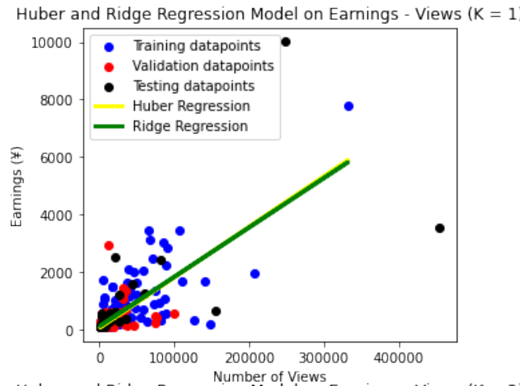
```
        tr_error["Ridge"].append(mean_squared_error(y_train,␣
↪y_pred_train_Ridge))
        val_error["Ridge"].append(mean_squared_error(y_val, y_pred_val_Ridge))

        # Start plotting
        axes[i].set_title("Huber and Ridge Regression Model on Earnings - " +␣
↪feature + " (K = " + str(i+1) + ")")
        axes[i].set_xlabel("Number of " + feature)
        axes[i].set_ylabel("Earnings (¥)")
        axes[i].scatter(X_train, y_train, color="blue", label = "Training␣
↪datapoints")
        axes[i].scatter(X_val, y_val, color="red", label = "Validation␣
↪datapoints")
        axes[i].scatter(X_test, y_test, color="black", label = "Testing␣
↪datapoints")
        axes[i].plot(X_train, y_pred_train_Huber, color="yellow", linewidth=3,␣
↪label = "Huber Regression")
        axes[i].plot(X_train, y_pred_train_Ridge, color="green", linewidth=3,␣
↪label = "Ridge Regression")
        axes[i].legend()
        i += 1

    # Printing out the result
    best_predictor_index_Huber = val_error["Huber"].
↪index(min(val_error["Huber"]))
    best_predictor_index_Ridge = val_error["Ridge"].
↪index(min(val_error["Ridge"]))
    y_pred_test_Huber = predictors["Huber"][best_predictor_index_Huber].
↪predict(X_test)
    y_pred_test_Ridge = predictors["Ridge"][best_predictor_index_Ridge].
↪predict(X_test)
    err_train = sum(tr_error["Huber"])/len(tr_error["Huber"])
    err_val = sum(val_error["Huber"])/len(val_error["Huber"])
    err_test = mean_squared_error(y_test, y_pred_test_Huber)

    print("Huber Regression. Error measured by MSE")
    print(f'Slopes for each K: {slope["Huber"]}')
    print(f'Slope by the best model predictor:␣
↪{slope["Huber"][best_predictor_index_Huber]}')
    print(f'Intercepts for each K: {intercept["Huber"]}')
    print(f'Intercept by the best model predictor:␣
↪{intercept["Huber"][best_predictor_index_Huber]}')
    print(f'Training error for each K: {tr_error["Huber"]}')
    print(f'Average training error: {err_train}')
    print(f'Training error by the best model predictor:␣
↪{tr_error["Huber"][best_predictor_index_Huber]}')
```

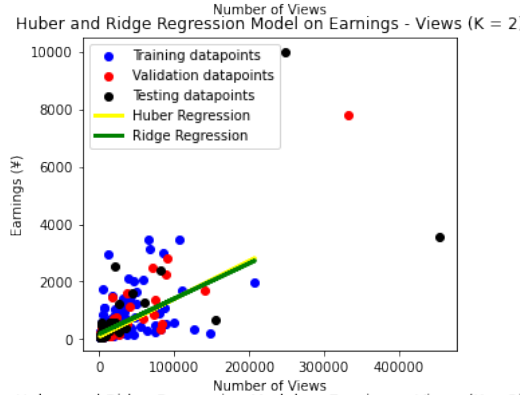
```
    print(f'Validation error for each K: {val_error["Huber"]}')
    print(f'Average validation error: {err_val}')
    print(f'Validation error by the best model predictor:␣
↪{val_error["Huber"][best_predictor_index_Huber]}')
    print(f'Testing error by the best model predictor: {err_test}\n')

    err_train = sum(tr_error["Ridge"])/len(tr_error["Ridge"])
    err_val = sum(val_error["Ridge"])/len(val_error["Ridge"])
    err_test = mean_squared_error(y_test, y_pred_test_Ridge)
    print("Ridge Regression. Error measured by MSE")
    print(f'Slopes for each K: {slope["Ridge"]}')
    print(f'Slope by the best model predictor:␣
↪{slope["Ridge"][best_predictor_index_Ridge]}')
    print(f'Intercepts for each K: {intercept["Ridge"]}')
    print(f'Intercept by the best model predictor:␣
↪{intercept["Ridge"][best_predictor_index_Ridge]}')
    print(f'Training error for each K: {tr_error["Ridge"]}')
    print(f'Average validation error: {err_val}')
    print(f'Training error by the best model predictor:␣
↪{tr_error["Ridge"][best_predictor_index_Ridge]}')
    print(f'Validation error for each K: {val_error["Ridge"]}')
    print(f'Average training error: {err_train}')
    print(f'Validation error by the best model predictor:␣
↪{val_error["Ridge"][best_predictor_index_Ridge]}')
    print(f'Testing error by the best model predictor: {err_test}\n')

    plt.show()
```

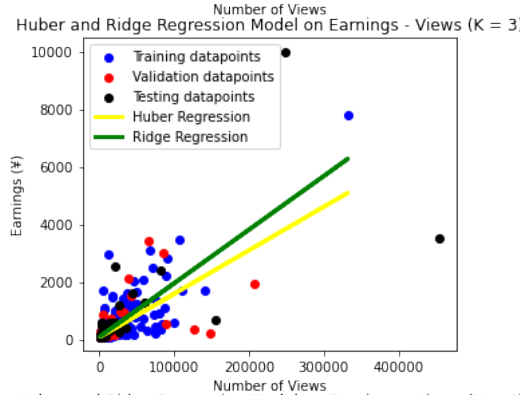
[9]:
```
# Comparing Huber and Ridge Regression Model on feature Views - label Earnings
X_views = df["Views"].to_numpy().reshape(-1,1)
y_earnings = earnings
feature = "Views"
model_comparison(X_views, y_earnings, feature)
```

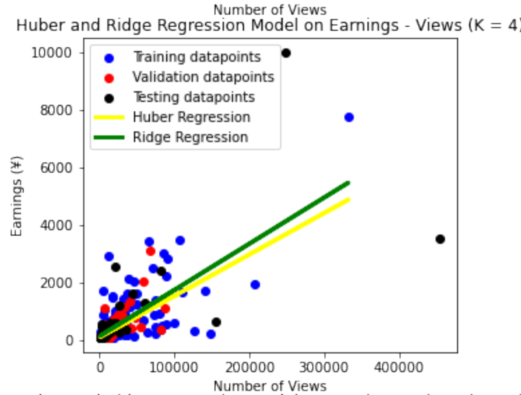
```
Huber Regression. Error measured by MSE
Slopes for each K: [0.017534499673096397, 0.01311903753088568,
0.015115781958991097, 0.014413660208038399, 0.021387415341738082]
Slope by the best model predictor: 0.014413660208038399
Intercepts for each K: [68.85232665236278, 91.50678268329034, 78.10118715618137,
88.05356873260702, 3.4000506344851755e-06]
Intercept by the best model predictor: 88.05356873260702
Training error for each K: [165997.6972830831, 164639.21833958148,
149925.02719566852, 188288.93766179125, 201386.59896352643]
Average training error: 174047.49588873016
Training error by the best model predictor: 188288.93766179125
Validation error for each K: [176166.82710417057, 240409.6608337491,
254023.99257064867, 109014.11301330589, 129830.72012304871]
```

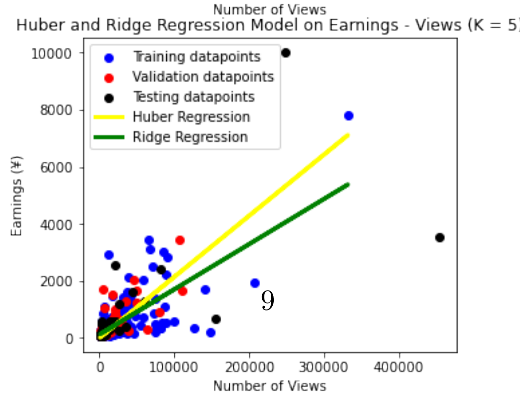
```
Average validation error: 181889.0627289846
Validation error by the best model predictor: 109014.11301330589
Testing error by the best model predictor: 1218286.7543276625

Ridge Regression. Error measured by MSE
Slopes for each K: [0.0171573198317369, 0.012258394513604803,
0.018633497069664554, 0.01606432289145588, 0.01580595472274676]
Slope by the best model predictor: 0.01606432289145588
Intercepts for each K: [121.5514030370453, 183.7844134781017, 92.3115005309242,
131.12396284600845, 123.20473956329391]
Intercept by the best model predictor: 131.12396284600845
Training error for each K: [163709.50433667115, 157965.31291004678,
136631.30400259345, 181006.80443436874, 174647.73581937424]
Average validation error: 192604.2658113158
Training error by the best model predictor: 181006.80443436874
Validation error for each K: [175587.54915896975, 253358.83209024803,
301786.5804571387, 102863.12358040737, 129425.24376981519]
Average training error: 162792.13230061086
Validation error by the best model predictor: 102863.12358040737
Testing error by the best model predictor: 1218836.3312658165
```


Huber and Ridge Regression Model on Earnings - Views (K = 1)
Training datapoints
Validation datapoints
Testing datapoints
Huber Regression
Ridge Regression
Earnings (¥)
Number of Views
0
2000
4000
6000
8000
10000
0
100000
200000
300000
400000


Huber and Ridge Regression Model on Earnings - Views (K = 2)
Training datapoints
Validation datapoints
Testing datapoints
Huber Regression
Ridge Regression
Earnings (¥)
Number of Views
0
2000
4000
6000
8000
10000
0
100000
200000
300000
400000

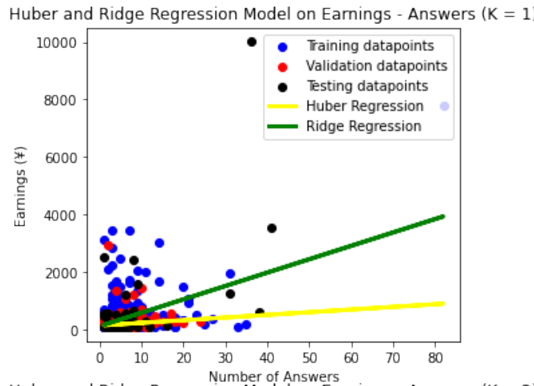

Huber and Ridge Regression Model on Earnings - Views (K = 3)
Training datapoints
Validation datapoints
Testing datapoints
Huber Regression
Ridge Regression
Earnings (¥)
Number of Views
0
2000
4000
6000
8000
10000
0
100000
200000
300000
400000

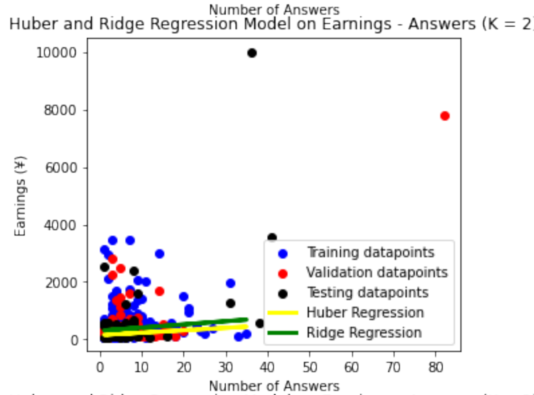

Huber and Ridge Regression Model on Earnings - Views (K = 4)
Training datapoints
Validation datapoints
Testing datapoints
Huber Regression
Ridge Regression
Earnings (¥)
Number of Views
0
2000
4000
6000
8000
10000
0
100000
200000
300000
400000

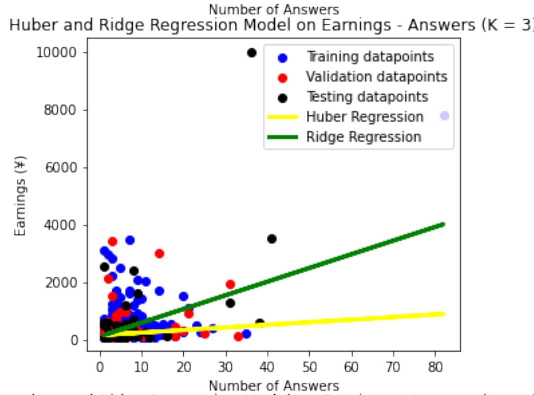

Huber and Ridge Regression Model on Earnings - Views (K = 5)
Training datapoints
Validation datapoints
Testing datapoints
Huber Regression
Ridge Regression
Earnings (¥)
Number of Views
0
2000
4000
6000
8000
10000
0
100000
200000
300000
400000

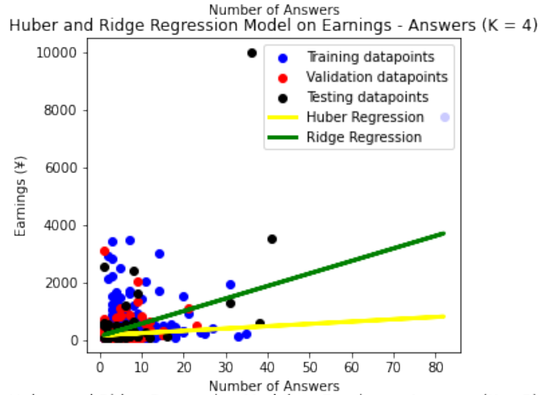
[10]:
```python
# Comparing Huber and Ridge Regression Model on feature Answers - label Earnings
X_views = df["Answers"].to_numpy().reshape(-1,1)
y_earnings = earnings
feature = "Answers"
model_comparison(X_views, y_earnings, feature)
```

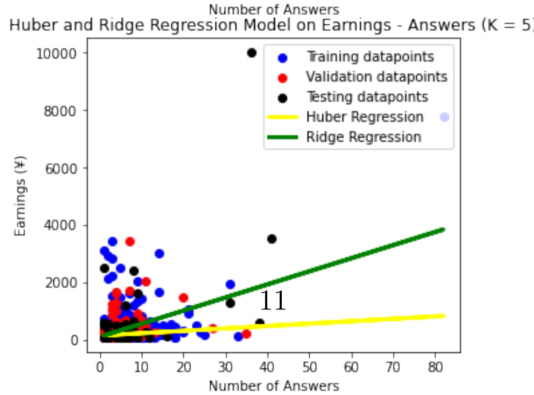
```
Huber Regression. Error measured by MSE
Slopes for each K: [9.249217372014055, 8.33326511888856, 9.000007097274038,
8.000000246814084, 8.333330674895905]
Slope by the best model predictor: 9.249217372014055
Intercepts for each K: [149.27113039436992, 151.33469762224425,
146.99999290002987, 157.9999981617545, 151.33338598430547]
Intercept by the best model predictor: 149.27113039436992
Training error for each K: [420880.2791054908, 256788.19490515735,
379984.37003062177, 410932.62718359794, 386950.34381525335]
Average training error: 371107.1630080242
Training error by the best model predictor: 420880.2791054908
Validation error for each K: [161739.34590453136, 835012.422947631,
335115.2390005152, 213800.0334341631, 314364.765473144]
Average validation error: 372006.36135199695
Validation error by the best model predictor: 161739.34590453136
Testing error by the best model predictor: 2305027.2499265973

Ridge Regression. Error measured by MSE
Slopes for each K: [46.48828481113721, 11.006621226272134, 47.555121620081245,
43.60082165370994, 45.56044607712424]
Slope by the best model predictor: 46.48828481113721
Intercepts for each K: [128.25341878802595, 302.23063670157165,
106.57322958863352, 131.12386538940115, 107.71064447955666]
Intercept by the best model predictor: 128.25341878802595
Training error for each K: [326376.171044674, 228865.91201221952,
291377.4882535789, 322616.7313831997, 300529.9388038214]
Average validation error: 357874.48778450646
Training error by the best model predictor: 326376.171044674
Validation error for each K: [198376.3666451799, 745544.2611290354,
339118.0451106158, 207584.66971260757, 298749.0963250937]
Average training error: 293953.2482994987
Validation error by the best model predictor: 198376.3666451799
Testing error by the best model predictor: 1705803.9433888039
```


Huber and Ridge Regression Model on Earnings - Answers (K = 1)
Training datapoints
Validation datapoints
Testing datapoints
Huber Regression
Ridge Regression
Earnings (¥)
Number of Answers


Huber and Ridge Regression Model on Earnings - Answers (K = 2)
Training datapoints
Validation datapoints
Testing datapoints
Huber Regression
Ridge Regression
Earnings (¥)
Number of Answers


Huber and Ridge Regression Model on Earnings - Answers (K = 3)
Training datapoints
Validation datapoints
Testing datapoints
Huber Regression
Ridge Regression
Earnings (¥)
Number of Answers


Huber and Ridge Regression Model on Earnings - Answers (K = 4)
Training datapoints
Validation datapoints
Testing datapoints
Huber Regression
Ridge Regression
Earnings (¥)
Number of Answers


Huber and Ridge Regression Model on Earnings - Answers (K = 5)
Training datapoints
Validation datapoints
Testing datapoints
Huber Regression
Ridge Regression
Earnings (¥)
Number of Answers

[15]:

```
copydf = df.copy()
# copydf['Topic'] = copydf['Topic'].map({"Social / News": 0, 'Health /␣
↪Psychology': 1, 'Culture / Politics': 2, 'Entertainment / Hobbies': 3, 'Life␣
↪/ Habit': 4, 'Technology / Internet': 5, 'Business / Career': 6, 'Love /␣
↪Relationship': 7, 'Education / Science': 8, 'Beauty / Fashion': 9})
copydf['Topic'] = copydf['Topic'].map({"Social / News": 0, 'Health /␣
↪Psychology': 1, 'Culture / Politics': 0, 'Entertainment / Hobbies': 2, 'Life␣
↪/ Habit': 1, 'Technology / Internet': 2, 'Business / Career': 0, 'Love /␣
↪Relationship': 1, 'Education / Science': 2, 'Beauty / Fashion': 2})
X_topics = copydf["Topic"].to_numpy()
y_earnings = earnings.reshape(-1,1)

tr_acc = { "Logistic": [], "Svm": [] }
val_acc = { "Logistic": [], "Svm": [] }
predictors = { "Logistic": [], "Svm": [] }

X_rem, X_test, y_rem, y_test = train_test_split(y_earnings, X_topics,␣
↪train_size=0.9, random_state = 42)
K = 5  # Number of splits
kf = KFold(n_splits=K, shuffle=True, random_state=42)    # Create a KFold␣
↪object with 'K' splits
i = 0
for train_indices, val_indices in kf.split(X_rem):
    X_train = X_rem[train_indices,:]    # Get the training set
    X_val = X_rem[val_indices,:]    # Get the validation set
    y_train = y_rem[train_indices]    # Get the training set
    y_val = y_rem[val_indices]    # Get the validation set

    # for Logistic Regression model training
    LogisticModel = LogisticRegression(max_iter = 1000)
    fitLogisticModel = LogisticModel.fit(X_train, y_train)
    predictors["Logistic"].append(fitLogisticModel)
    y_pred_train_Logistic = fitLogisticModel.predict(X_train)
    # for Logistic Regression validation
    y_pred_val_Logistic = fitLogisticModel.predict(X_val)
    tr_acc["Logistic"].append(accuracy_score(y_train, y_pred_train_Logistic))
    val_acc["Logistic"].append(accuracy_score(y_val, y_pred_val_Logistic))

    # for SVM Regression model training
    SvmModel = SVC(max_iter = 1000)
    fitSvmModel = SvmModel.fit(X_train, y_train)
    predictors["Svm"].append(fitSvmModel)
    y_pred_train_Svm = fitSvmModel.predict(X_train)
    # for SVM Regression validation
```

```
    y_pred_val_Svm = fitSvmModel.predict(X_val)
    tr_acc["Svm"].append(accuracy_score(y_train, y_pred_train_Svm))
    val_acc["Svm"].append(accuracy_score(y_val, y_pred_val_Svm))

best_predictor_index_Logistic = val_acc["Logistic"].
 ↪index(max(val_acc["Logistic"]))
best_predictor_index_Svm = val_acc["Svm"].index(max(val_acc["Svm"]))
y_pred_test_Logistic = predictors["Logistic"][best_predictor_index_Logistic].
 ↪predict(X_test)
y_pred_test_Svm = predictors["Svm"][best_predictor_index_Svm].predict(X_test)

acc_train_Logistic = sum(tr_acc["Logistic"])/len(tr_acc["Logistic"])
acc_val_Logistic = sum(val_acc["Logistic"])/len(val_acc["Logistic"])
acc_test_Logistic = accuracy_score(y_test, y_pred_test_Logistic)
print("Logistic Regression. Accuracy score measured by accuracy_score")
print(f'Training accuracy for each K: {tr_acc["Logistic"]}')
print(f'Validation accuracy for each K: {val_acc["Logistic"]}')
print(f'Average training accuracy: {acc_train_Logistic}')
print(f'Average validation accuracy: {acc_val_Logistic}')
print(f'Testing score by the best model predictor: {acc_test_Logistic}\n')

acc_train_Svm = sum(tr_acc["Svm"])/len(tr_acc["Svm"])
acc_val_Svm = sum(val_acc["Svm"])/len(val_acc["Svm"])
acc_test_Svm = accuracy_score(y_test, y_pred_test_Svm)
print("SVM Regression. Accuracy score measured by accuracy_score")
print(f'Training accuracy for each K: {tr_acc["Svm"]}')
print(f'Validation accuracy for each K: {val_acc["Svm"]}')
print(f'Average training accuracy: {acc_train_Svm}')
print(f'Average validation accuracy: {acc_val_Svm}')
print(f'Testing score by the best model predictor: {acc_test_Svm}\n')

earnings_test = np.arange(0, 10001, 20)
earnings_predict = predictors["Svm"][best_predictor_index_Logistic].
 ↪predict(earnings_test.reshape(-1,1))
np.set_printoptions(threshold = np.inf)
print(earnings_predict)
# plot bar results
acc_Logistic = list[acc_train_Logistic, acc_val_Logistic, acc_test_Logistic]
acc_Svm = list[acc_train_Svm, acc_val_Svm, acc_test_Svm]
acc_train = [acc_train_Logistic, acc_train_Svm]
acc_val = [acc_val_Logistic, acc_val_Svm]
acc_test = [acc_test_Logistic, acc_test_Svm]
X = np.arange(2)
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(X - 0.15, acc_train, color = 'b', width = 0.15, label = "Average␣
 ↪training accuracy")
```

```
ax.bar(X, acc_val, color = 'g', width = 0.15, label = "Average validation␣
 ↪accuracy")
ax.bar(X + 0.15, acc_test, color = 'r', width = 0.15, label = "Best predictor␣
 ↪testing accuracy")
ax.set_xticks(X, labels = ("Logistic Regression","SVC"))
#ax.set_xticklabels(["LogisticRegression","SVC"])
ax.set_ylabel("Accuracies")
ax.set_title("Accuracy score of Logistic and SVM Regression Models")
ax.legend(loc="lower center")
```

```
Logistic Regression. Accuracy score measured by accuracy_score
Training accuracy for each K: [0.40555555555555556, 0.37222222222222223, 0.4,
0.38333333333333336, 0.38055555555555554]
Validation accuracy for each K: [0.3111111111111111, 0.43333333333333335,
0.3333333333333333, 0.3888888888888889, 0.23333333333333334]
Average training accuracy: 0.3883333333333333
Average validation accuracy: 0.33999999999999997
Testing score by the best model predictor: 0.4

SVM Regression. Accuracy score measured by accuracy_score
Training accuracy for each K: [0.40555555555555556, 0.3972222222222222,
0.40555555555555556, 0.3861111111111111, 0.41388888888888886]
Validation accuracy for each K: [0.3111111111111111, 0.36666666666666664,
0.3111111111111111, 0.3888888888888889, 0.3333333333333333]
Average training accuracy: 0.40166666666666667
Average validation accuracy: 0.3422222222222222
Testing score by the best model predictor: 0.4

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[15]: <matplotlib.legend.Legend at 0x7f96468653d0>
```

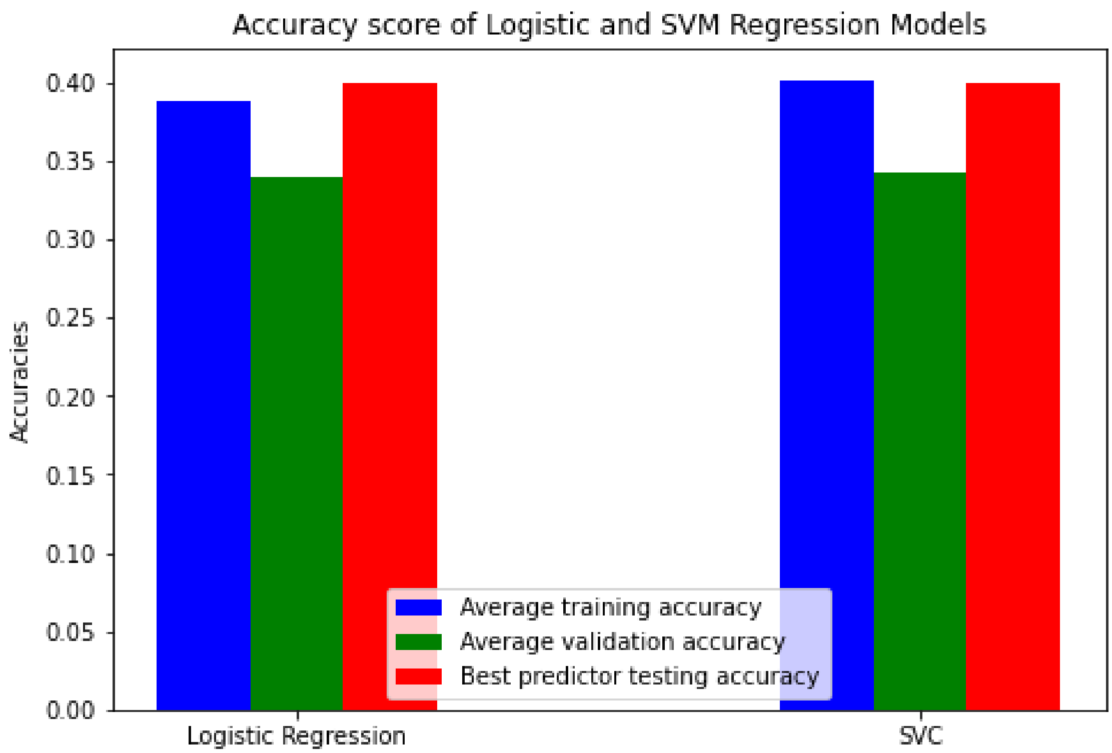

Accuracy score of Logistic and SVM Regression Models
Accuracies
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Average training accuracy
Average validation accuracy
Best predictor testing accuracy
Logistic Regression
SVC