cs441-sp24-hw2-starter

February 20, 2024

0.1 CS441: Applied ML - HW 2

0.1.1 Parts 1-2: MNIST

Include all the code for generating MNIST results below

```
[80]: # initialization code
      import numpy as np
      from keras.datasets import mnist
      %matplotlib inline
      from matplotlib import pyplot as plt
      from scipy import stats
      from sklearn.linear model import LogisticRegression
      import cache_magic
      def load mnist():
        111
        Loads, reshapes, and normalizes the data
        (x_train, y_train), (x_test, y_test) = mnist.load_data() # loads MNIST data
        x_train = np.reshape(x_train, (len(x_train), 28*28)) # reformat to 768-d_
       \rightarrowvectors
        x_test = np.reshape(x_test, (len(x_test), 28*28))
        maxval = x_train.max()
        x_train = x_train/maxval # normalize values to range from 0 to 1
        x test = x test/maxval
        return (x_train, y_train), (x_test, y_test)
      def display_mnist(x, subplot_rows=1, subplot_cols=1):
        Displays one or more examples in a row or a grid
        if subplot_rows>1 or subplot_cols>1:
          fig, ax = plt.subplots(subplot_rows, subplot_cols, figsize=(15,15))
          for i in np.arange(len(x)):
            ax[i].imshow(np.reshape(x[i], (28,28)), cmap='gray')
            ax[i].axis('off')
            plt.imshow(np.reshape(x, (28,28)), cmap='gray')
```

```
plt.axis('off')
plt.show()
```

0.1.2 Part 1: PCA and Data Compression

```
[81]: from sklearn.decomposition import PCA
   import matplotlib.pyplot as plt

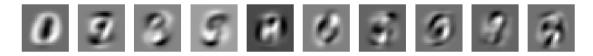
   (x_train, y_train), (x_test, y_test) = load_mnist()

# Compute the first 10 principal components using x_train

%cache pcala = PCA(n_components=10).fit(x_train)

print(pcala.components_.shape)
# Display First 10 Components
display_mnist(pcala.components_, subplot_rows=1, subplot_cols=10)
```

Loading cached value for variable 'pca1a'. Time since caching: 8 days, 1:38:03.816843 (10, 784)

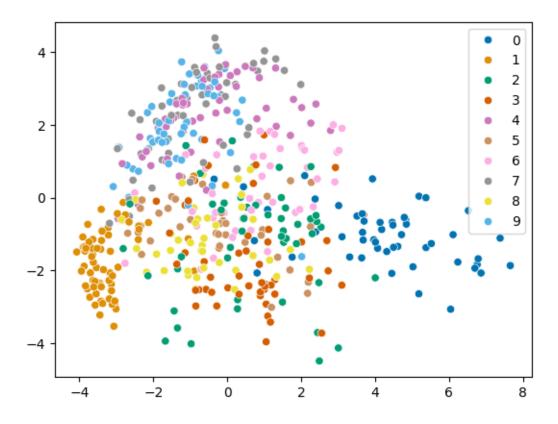


```
[82]: # Scatter plot of first two PCA dimensions
import seaborn as sns

# use pca.transform
%cache pca1b = PCA(n_components=2).fit(x_train)
x = pca1b.transform(x_train[:500])
ind = np.arange(500)
sns.scatterplot(x=x[ind,0],y=x[ind,1], hue=y_train[ind], palette="colorblind")

Loading cached value for variable 'pca1b'. Time since caching: 8 days,
1:40:06.955217
```

[82]: <Axes: >

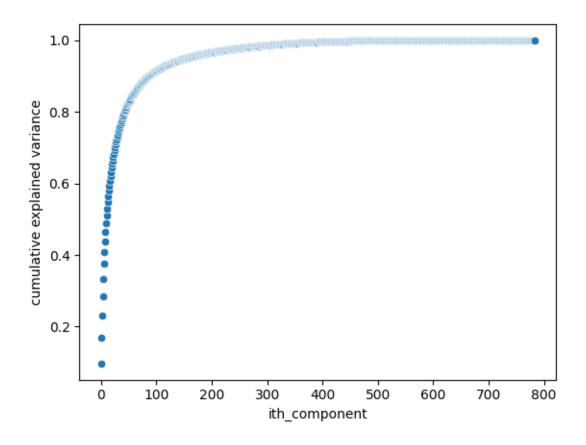


```
[83]: # Plot cumulative explained variance ratio
    # cumsum and pca.explained_variance_ratio_ will be useful

%cache pca1c = PCA().fit(x_train)
    cumul = np.cumsum(pca1c.explained_variance_ratio_)
    sns.scatterplot(
        data = {
          "ith_component": np.arange(0, len(cumul), 1),
          "cumulative explained variance": cumul
        },
        x = "ith_component",
        y = "cumulative explained variance"
)
```

Loading cached value for variable 'pca1c'. Time since caching: 8 days, 1:37:55.480961

[83]: <Axes: xlabel='ith_component', ylabel='cumulative explained variance'>



```
[84]: # Select number of dimensions that explains 90% of variance, according to your
       ⇔plot above
      # !apt install libomp-dev > /dev/null 2>&1
      # !pip install faiss-cpu > /dev/null 2>&1
      import faiss
      import time
      # plus 1 because of 0 indexing
      M = np.argwhere(cumul >= 0.9)[0].item() + 1
      print(f"M = {M}")
      # compress training data and test data
      %cache pcald = PCA(n_components=M).fit(x_train)
      compressed_train, compressed_test = pcald.transform(x_train), pcald.
       ⇔transform(x_test)
      def create_and_add(dim, data):
          idx = faiss.IndexFlatL2(dim)
          idx.add(data)
          return idx
      # Get time and error when using original features with brute force 1-NN
```

```
%cache original_index = create_and_add(x_train.shape[1], x_train)
      t1 = time.time()
      dist, prediction = original_index.search(x_test, 1)
      t2 = time.time()
      timing = t2 - t1
      # prediction = y_train[prediction]
      # error = prediction[prediction != y_test.reshape(-1, 1)].sum() / _ _ _ _
      \hookrightarrow len(prediction) * 100
      error = np.mean(y_train[prediction.flatten()] != y_test) * 100
      print(f"original error = {error}% | time = {timing}")
      # print(np.mean(dist))
      # Get time and error when using compressed features with brute force 1-NN
      %cache comp_index = create_and_add(compressed_train.shape[1], compressed_train)
      t1 = time.time()
      dist, prediction = comp_index.search(compressed_test, 1)
      t2 = time.time()
      timing = t2 - t1
      # prediction = y_train[prediction]
      error = np.mean(y_train[prediction.flatten()] != y_test) * 100
      print(f"compressed error = {error}% | time = {timing}")
      # print(np.mean(dist))
     M = 87
     Loading cached value for variable 'pca1d'. Time since caching: 8 days,
     1:37:52.756670
     Loading cached value for variable 'original index'. Time since caching: 8 days,
     1:37:50.756619
     original error = 3.09\% | time = 5.727076530456543
     Loading cached value for variable 'comp_index'. Time since caching: 8 days,
     1:37:50.332103
     compressed error = 2.68% | time = 1.317983627319336
[85]: %cache
     <IPython.core.display.HTML object>
     0.1.3 Part 2: MNIST Classification with Linear Models
```

```
[86]: from sklearn.linear_model import LogisticRegression from sklearn import svm from sklearn.metrics import accuracy_score
```

LLR/SVM vs training size

```
[87]: # LLR sizes = [100, 1000, 10000, 60000]
```

Loading cached value for variable 'llr_estimators'. Time since caching: 8 days, 1:37:11.062065 [0.32499999999999, 0.13639999999999, 0.09499999999999, 0.07389999999997]

Loading cached value for variable 'svm_estimators'. Time since caching: 7 days, 23:17:33.032995 [0.3235, 0.1611000000000000, 0.111199999999997, 0.0817]

Error visualization

```
[89]: scores = llr_estimators[-1].predict_proba(x_test)
      llrhigh, llrlow = [], []
      for cls in range(10):
          # get samples with true label of class
          cls_sample = x_test[y_test == cls]
          # get their scores
          cls_sample_scores = scores[y_test == cls][:, cls]
          # show
          llrhigh.append(cls_sample[np.argmax(cls_sample_scores)])
          llrlow.append(cls_sample[np.argmin(cls_sample_scores)])
      print("LLR high and low confidence")
      display_mnist(llrhigh, subplot_rows=1, subplot_cols=10)
      display_mnist(llrlow, subplot_rows=1, subplot_cols=10)
      scores = svm_estimators[-1].decision_function(x_test)
      svmhigh, svmlow = [], []
      for cls in range(10):
          # get samples with true label of class
          cls_sample = x_test[y_test == cls]
          # get their scores
```

```
cls_sample_scores = scores[y_test == cls][:, cls]
# show
svmhigh.append(cls_sample[np.argmax(cls_sample_scores)])
svmlow.append(cls_sample[np.argmin(cls_sample_scores)])

print("SVM high and low confidence")
display_mnist(svmhigh, subplot_rows=1, subplot_cols=10)
display_mnist(svmlow, subplot_rows=1, subplot_cols=10)
```

LLR high and low confidence



SVM high and low confidence



Parameter selection

```
[90]: # Try multiple C parameters, select one that minimizes validation error
# Often, you need to try a few values and see those results to determine what_
other values to try

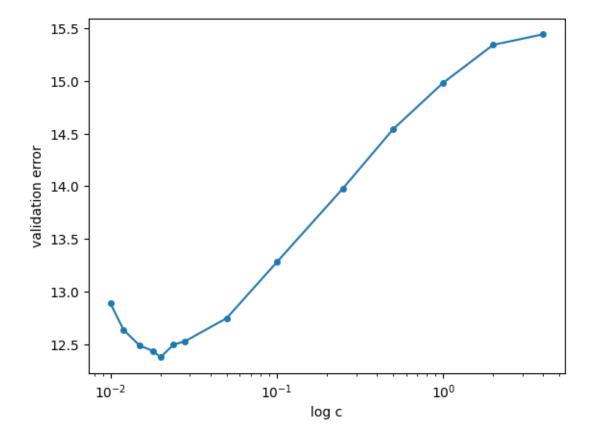
get_error = lambda pred, y: (pred != y).sum() / len(y) * 100

C = [0.01, 0.012, 0.015, 0.018, 0.02, 0.024, 0.028, 0.05, 0.1, 0.25, 0.5, 1, 2, 4]

x_train2c, x_val2c = x_train[:1000], x_train[50000:]
```

```
y_train2c, y_val2c = y_train[:1000], y_train[50000:]
val_err = []
for c in C:
    model = svm.LinearSVC(max_iter=10000, dual='auto', C=c)
    model.fit(x_train2c, y_train2c)
    val_err.append(get_error(model.predict(x_val2c), y_val2c))
plt.semilogx(C, val_err, marker='o', markersize=4)
plt.xlabel('log c')
plt.ylabel('validation error')
```

[90]: Text(0, 0.5, 'validation error')



```
[91]: # Get test result for selected parameter
%cache best_svm_model = svm.LinearSVC(max_iter=10000, dual='auto', C=0.02).

fit(x_train2c, y_train2c)
print(f"Validation error: {get_error(best_svm_model.predict(x_val2c),__
y_val2c)}")
print(f"Test error: {get_error(best_svm_model.predict(x_test), y_test)}")
```

Loading cached value for variable 'best_svm_model'. Time since caching: 7 days, 15:46:20.024406

0.2 Part 3: Temperature Regression

```
[92]: import numpy as np
      # from google.colab import drive
      %matplotlib inline
      from matplotlib import pyplot as plt
      from sklearn.linear_model import Ridge
      from sklearn.linear_model import Lasso
      # load data (modify to match your data directory or comment)
      def load temp data():
       datadir = "./"
       T = np.load(datadir + 'temperature_data.npz')
       x_train, y_train, x_val, y_val, x_test, y_test, dates_train, dates_val,_
       dates_test, feature_to_city, feature_to_day = \
       T['x_train'], T['y_train'], T['x_val'], T['y_val'], T['x_test'], T['y_test'],
       →T['dates_train'], T['dates_val'], T['dates_test'], T['feature_to_city'], □

¬T['feature_to_day']
       return (x_train, y_train, x_val, y_val, x_test, y_test, dates_train,_
       ⇒dates_val, dates_test, feature_to_city, feature_to_day)
      # plot one data point for listed cities and target date
      def plot_temps(x, y, cities, feature_to_city, feature_to_day, target_date):
       nc = len(cities)
       ndays = 5
        xplot = np.array([-5, -4, -3, -2, -1])
        yplot = np.zeros((nc,ndays))
       for f in np.arange(len(x)):
          for c in np.arange(nc):
            if cities[c] == feature to city[f]:
              yplot[feature_to_day[f]+ndays,c] = x[f]
       plt.plot(xplot,yplot)
       plt.legend(cities)
       plt.plot(0, y, 'b*', markersize=10)
       plt.title('Predict Temp for Cleveland on ' + target_date)
       plt.xlabel('Day')
       plt.ylabel('Avg Temp (C)')
       plt.show()
```

```
[93]: # load data
(x_train, y_train, x_val, y_val, x_test, y_test, dates_train, dates_val,u_dates_test, feature_to_city, feature_to_day) = load_temp_data()
''' Data format:
```

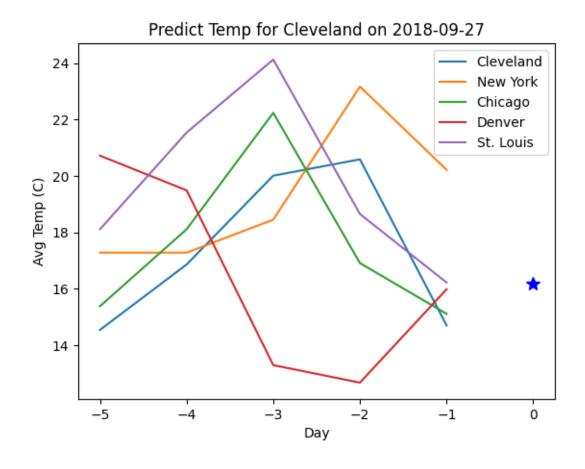
```
x\_train, y\_train: features and target value for each training sample \sqcup
 \hookrightarrow (used to fit model)
      x_val, y_val: features and target value for each validation sample (used
 \hookrightarrowto select hyperparameters, such as regularization and K)
      x_{test}, y_{test}: features and target value for each test sample (used to_\sqcup
 ⇔evaluate final performance)
      dates_xxx: date of the target value for the corresponding sample
      feature_to_city: maps from a feature number to the city
      feature_to_day: maps from a feature number to a day relative to the_
 \hookrightarrow target value, e.g. -2 means two days before
      Note: 361 is the temperature of Cleveland on the previous day
111
f = 361
print('Feature {}: city = {}, day= {}'.format(f,feature_to_city[f],__

→feature_to_day[f]))
baseline_rmse = np.sqrt(np.mean((y_val[1:]-y_val[:-1])**2)) # root mean squared_
\rightarrow error
print('Baseline - prediction using previous day: RMSE={}'.format(baseline_rmse))
# plot first two x/y for val
plot_temps(x_val[0], y_val[0], ['Cleveland', 'New York', 'Chicago', 'Denver', _

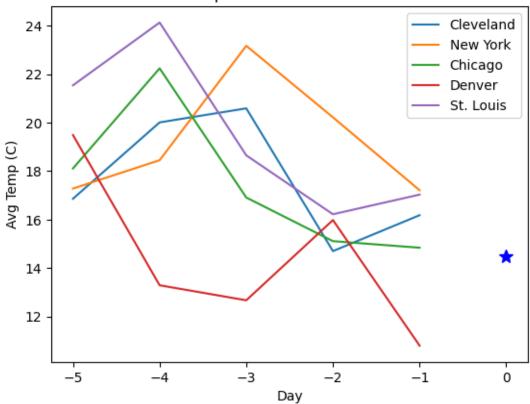
¬'St. Louis'], feature_to_city, feature_to_day, dates_val[0])

plot_temps(x_val[1], y_val[1], ['Cleveland', 'New York', 'Chicago', 'Denver', _
```

Feature 361: city = Cleveland, day= -1
Baseline - prediction using previous day: RMSE=3.460601246750482







Linear regression test

```
[95]: F = 361
    from sklearn.metrics import root_mean_squared_error
    # linear regression (use Ridge)
    # original features
    %cache original_ridge = Ridge().fit(x_train, y_train)
```

```
print(f"original features rmse: {np.sqrt(np.mean((original_ridge.
       →predict(x_test) - y_test) ** 2))}")
      # normalized features
      (x_train_norm, y_train_norm), (x_test_norm, y_test_norm) = ___
       ⊸normalize_features(x_train, y_train, F), normalize_features(x_test, y_test, u_
      %cache normalized_ridge = Ridge().fit(x_train_norm, y_train_norm)
      print(f"normalized features rmse: {np.sqrt(np.mean((normalized ridge.
       →predict(x_test_norm) - y_test_norm) ** 2))}")
     Loading cached value for variable 'original_ridge'. Time since caching: 6 days,
     0:30:16.487390
     original features rmse: 2.160860526080926
     Loading cached value for variable 'normalized ridge'. Time since caching: 6
     days, 0:22:20.693291
     normalized features rmse: 2.1630698027573665
     Feature selection
[96]: # feature analysis (select important features using Lasso)
      lasso = Lasso().fit(x_train, y_train)
      lasso_indices = [(i, v) for i, v in enumerate(np.abs(lasso.coef_)) if v > 0.001]
      lasso_indices.sort(key = lambda x: x[1], reverse=True)
      top10 indices = [x[0] for x in lasso indices[:10]]
      print(f"Top 10: {top10_indices}")
      print(f"Top 10 cities: {[feature_to_city[x] for x in top10_indices]}")
      print(f"Top 10 days: {[feature_to_day[x] for x in top10_indices]}")
      # predict using best features
      selected_indices = [x[0] for x in lasso_indices]
      root_mean_squared_error(
          Ridge().fit(
              np.take(x_train, selected_indices, axis=1), y_train)
              .predict(np.take(x_test, selected_indices, axis=1))
          , y_test
      )
     Top 10: [334, 347, 405, 366, 361, 307, 367, 264, 9, 236]
     Top 10 cities: ['Chicago', 'Minneapolis', 'Grand Rapids', 'Kansas City',
     'Cleveland', 'Omaha', 'Indianapolis', 'Minneapolis', 'Boston', 'Springfield']
     Top 10 days: [-1, -1, -1, -1, -1, -2, -1, -2, -5, -3]
[96]: 2.0579879892446384
[97]: %cache
```

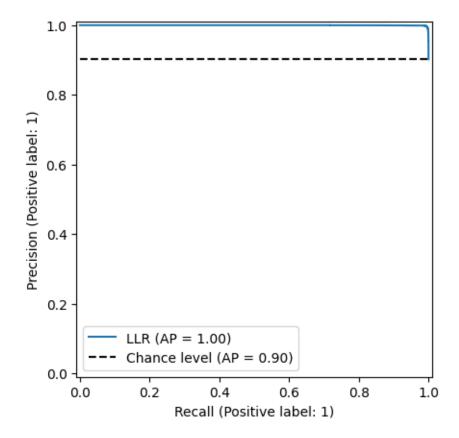
<IPython.core.display.HTML object>

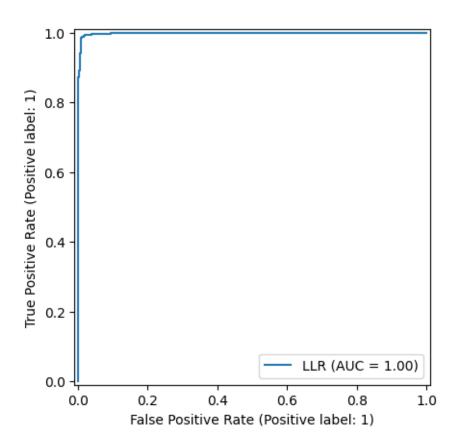
0.3 Part 4: Stretch Goals

Include all your code used for any stretch goals in this section. Add headings where appropriate.

a) PR and ROC curves

[98]: <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1da02c62b90>



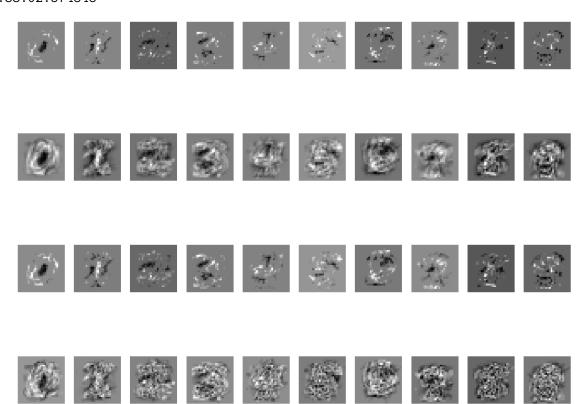


b) Visualize weights

Loading cached value for variable 'p4bllrl1'. Time since caching: 5 days, 18:34:20.956202

Loading cached value for variable 'p4bllrl2'. Time since caching: 5 days, 18:34:17.953454

Loading cached value for variable 'p4bllrel'. Time since caching: 5 days, 18:33:02.574848

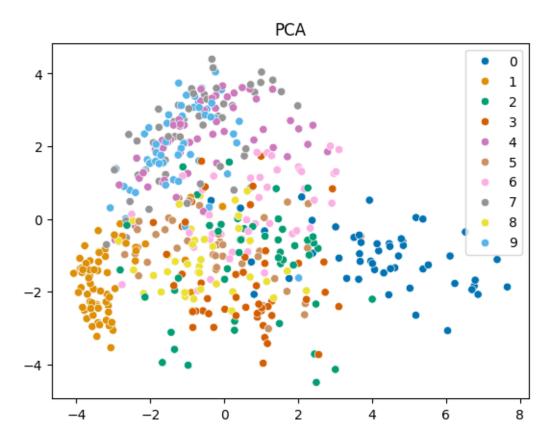


c) Other embeddings

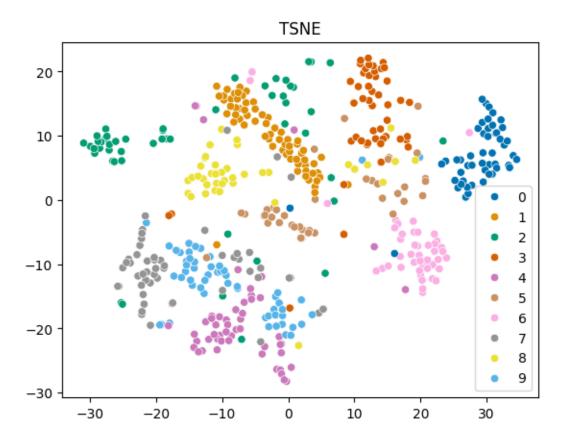
```
[100]: x = pca1b.transform(x_train[:500])
ind = np.arange(500)
sns.scatterplot(x=x[ind,0],y=x[ind,1], hue=y_train[ind], palette="colorblind").

set(title='PCA')
```

[100]: [Text(0.5, 1.0, 'PCA')]

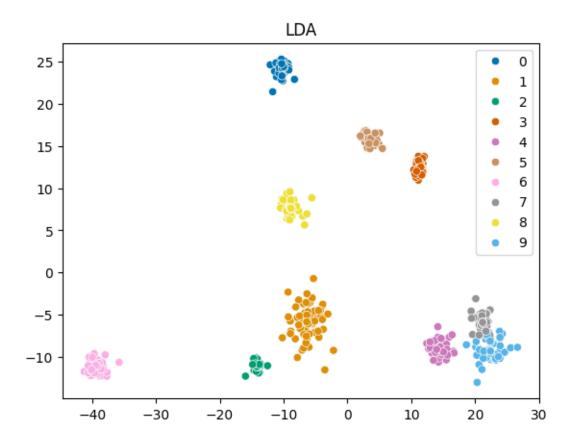


[101]: [Text(0.5, 1.0, 'TSNE')]



```
[102]: from sklearn.discriminant_analysis import LinearDiscriminantAnalysis p4clda = LinearDiscriminantAnalysis(n_components=2).fit(x_train[:500], y_train[: $\infty 500])  
x = p4clda.transform(x_train[:500])  
sns.scatterplot(x=x[ind,0],y=x[ind,1], hue=y_train[ind], palette="colorblind").  
$\infty set(title='LDA')$
```

[102]: [Text(0.5, 1.0, 'LDA')]



e) SVM with RBF Kernel

```
[0.675, 0.8636, 0.905, 0.9261]
Loading cached value for variable 'svmrbf_estimators'. Time since caching: 5 days, 17:37:32.071795
Loading cached value for variable 'svmrbfscores'. Time since caching: 5 days, 17:30:58.110247
[0.6559, 0.9083, 0.9594, 0.9792]
```

```
[104]: %cache
```

<IPython.core.display.HTML object>

```
[105]: | # from https://gist.github.com/jonathanagustin/b67b97ef12c53a8dec27b343dca4abba
      # install can take a minute
      # import os
       # # @title Convert Notebook to PDF. Save Notebook to given directory
       # NOTEBOOKS_DIR = "/content/drive/My Drive/CS441/24SP/hw2" # @param {type:
      # NOTEBOOK NAME = "CS441 SP24 HW2 Solution.ipynb" # @param {type:"string"}
      #__
        ⇔#----
      # from google.colab import drive
       # drive.mount("/content/drive/", force_remount=True)
      # NOTEBOOK_PATH = f"{NOTEBOOKS_DIR}/{NOTEBOOK_NAME}"
       # assert os.path.exists(NOTEBOOK_PATH), f"NOTEBOOK_NOT FOUND: {NOTEBOOK_PATH}"
       # !apt install -y texlive-xetex texlive-fonts-recommended texlive-plain-generic_
       →> /dev/null 2>&1
      # !jupyter nbconvert "$NOTEBOOK_PATH" --to pdf > /dev/null 2>&1
      # NOTEBOOK PDF = NOTEBOOK PATH.rsplit('.', 1)[0] + '.pdf'
       # assert os.path.exists(NOTEBOOK_PDF), f"ERROR MAKING PDF: {NOTEBOOK_PDF}"
       # print(f"PDF CREATED: {NOTEBOOK_PDF}")
```