COMS6998_015 Prac Deep Learning System HW1

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Github:

- Everything used to produce this notebook: https://github.com/AllenChenCU/coms6998-dl-sys/tree/main/hw1
- All theory and code are in this notebook, except the code for problem 3. See the below link for problem 3 code.
- Code for Problem 3: https://github.com/AllenChenCU/coms6998-dl-sys/blob/main/hw1/prob3_code.py

Problem 1 - Bias Variance Tradeoff, Regularization

1.1 Derive the bias-variance decomposition for a regression problem

$\mathrm{MSE} = \frac{1}{t}\sum_{i=1}^{t}(f(x_i)+\epsilon-g(x_i))^2$

$\mathbb{E}[\mathrm{MSE}] = \mathbb{E}[\frac{1}{t}\sum_{i=1}^{t}(f(x_i)+\epsilon-g(x_i))^2]$

$\mathbb{E}[\mathrm{MSE}] = \frac{1}{t}\mathbb{E}[\sum_{i=1}^{t}(f(x_i)-g(x_i))^2+2(f(x_i)-g(x_i))\epsilon+\epsilon^2]$

$\mathbb{E}[\mathrm{MSE}] = \frac{1}{t}\mathbb{E}[\sum_{i=1}^{t}(f(x_i)-g(x_i))^2]+\mathbb{E}[\epsilon^2]$

$\mathbb{E}[\mathrm{MSE}] = \frac{1}{t}\mathbb{E}[\sum_{i=1}^{t}(f(x_i)-g(x_i))^2]+\sigma^2$

$\mathbb{E}[\mathrm{MSE}] = \frac{1}{t}\mathbb{E}[\sum_{i=1}^{t}(f(x_i)-\mathbb{E}[g(x_i)]+\mathbb{E}[g(x_i)]-g(x_i))^2]+\sigma^2$

$\mathbb{E}[\mathrm{MSE}] = \frac{1}{t}\mathbb{E}[\sum_{i=1}^{t}(f(x_i)-\mathbb{E}[g(x_i)])^2+2(f(x_i)-\mathbb{E}[g(x_i)])(\mathbb{E}[g(x_i)]-g(x_i))+(\mathbb{E}$

$\mathbb{E}[\mathrm{MSE}] = \frac{1}{t}\mathbb{E}[\sum_{i=1}^{t}(f(x_i)-\mathbb{E}[g(x_i)])^2+(\mathbb{E}[g(x_i)]-g(x_i))^2]+\sigma^2$

$\mathbb{E}[\mathrm{MSE}] = \frac{1}{t}\sum_{i=1}^{t}(f(x_i)-\mathbb{E}[g(x_i)])^2+\frac{1}{t}\mathbb{E}[\sum_{i=1}^{t}(\mathbb{E}[g(x_i)]-g(x_i))^2]+\sigma^2$

$\mathbb{E}[\mathrm{MSE}] = Bias^2+Variance+Noise$

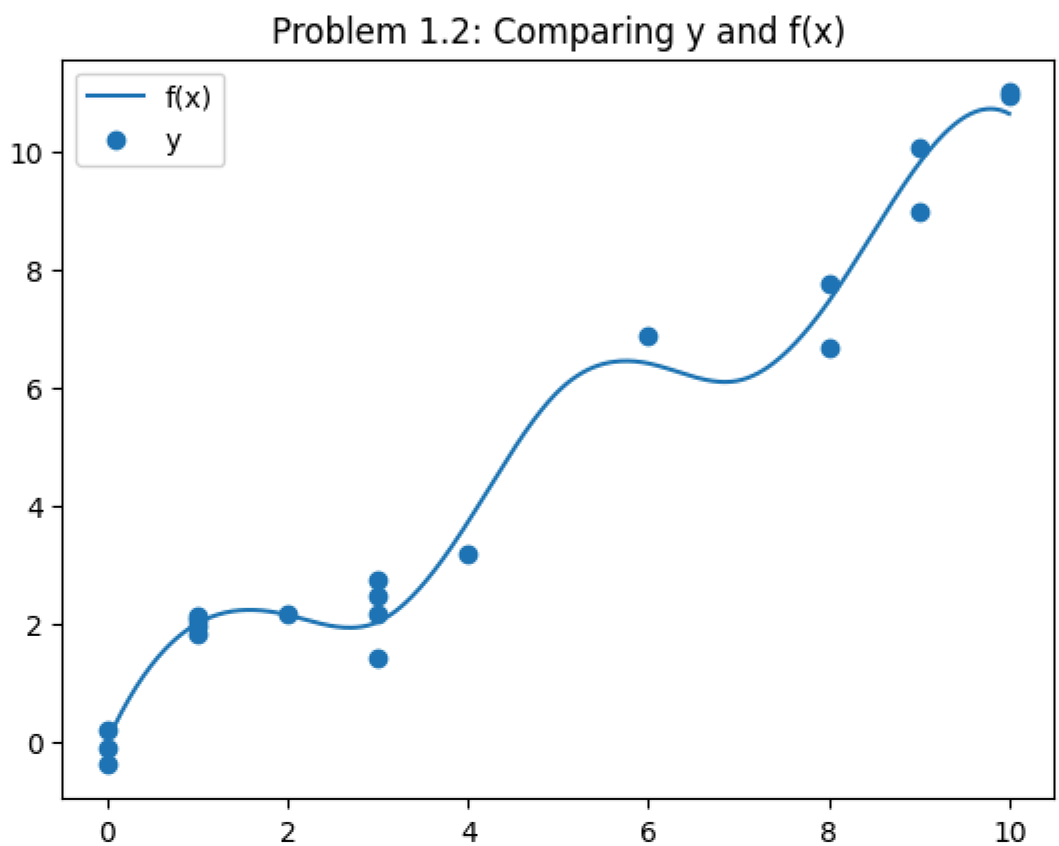
1.2 Scatter plot for y and f(x)

$y(x) = x + sin(1.5x) + N(0, 0.3)$

$f(x) = x + sin(1.5x)$

In [1]:
```
%load_ext autoreload
%autoreload 2

import numpy as np
import pandas as pd
import random
import math
import matplotlib.pyplot as plt
from scipy.interpolate import interp1d

random.seed(42)

def y_func(x, mu, sigma):
    noise = random.gauss(mu=mu, sigma=sigma)
    return x + math.sin(1.5*x) + noise

def f_func(x):
    return x + math.sin(1.5*x)

MU = 0
SIGMA = math.sqrt(0.3)
N = 20
XMAX = 10

X = [random.randint(0, XMAX) for _ in range(N)]
Y = [y_func(x, MU, SIGMA) for x in X]
F = [f_func(x) for x in X]

# display dataset
dataset = pd.DataFrame({"x": X, "y": Y, "f(x)": F})
print(dataset)

# Plot
X_1 = np.arange(XMAX + 1)
F_1 = [f_func(x) for x in X_1]
x_smooth = np.linspace(0, XMAX, 500)
smooth_func = interp1d(X_1, F_1, kind='cubic')

plt.title("Problem 1.2: Comparing y and f(x)")
plt.plot(x_smooth, smooth_func(x_smooth), label="f(x)")
plt.scatter(X, Y, label="y")
plt.legend()
plt.show()
```

```
     x          y       f(x)
0   10  11.009942  10.650288
1    1   2.058022   1.997495
2    0  -0.404395   0.000000
3    4   3.164831   3.720585
4    3   2.157397   2.022470
5    3   2.740578   2.022470
6    2   2.163936   2.141120
7    1   1.939259   1.997495
8   10  10.941554  10.650288
9    8   6.667288   7.463427
10   1   1.826454   1.997495
11   9  10.072367   9.803784
12   6   6.890502   6.412118
13   0  -0.131798   0.000000
14   0   0.206272   0.000000
15   1   2.133447   1.997495
16   3   2.450968   2.022470
17   3   1.412733   2.022470
18   8   7.774671   7.463427
19   9   8.974247   9.803784
```



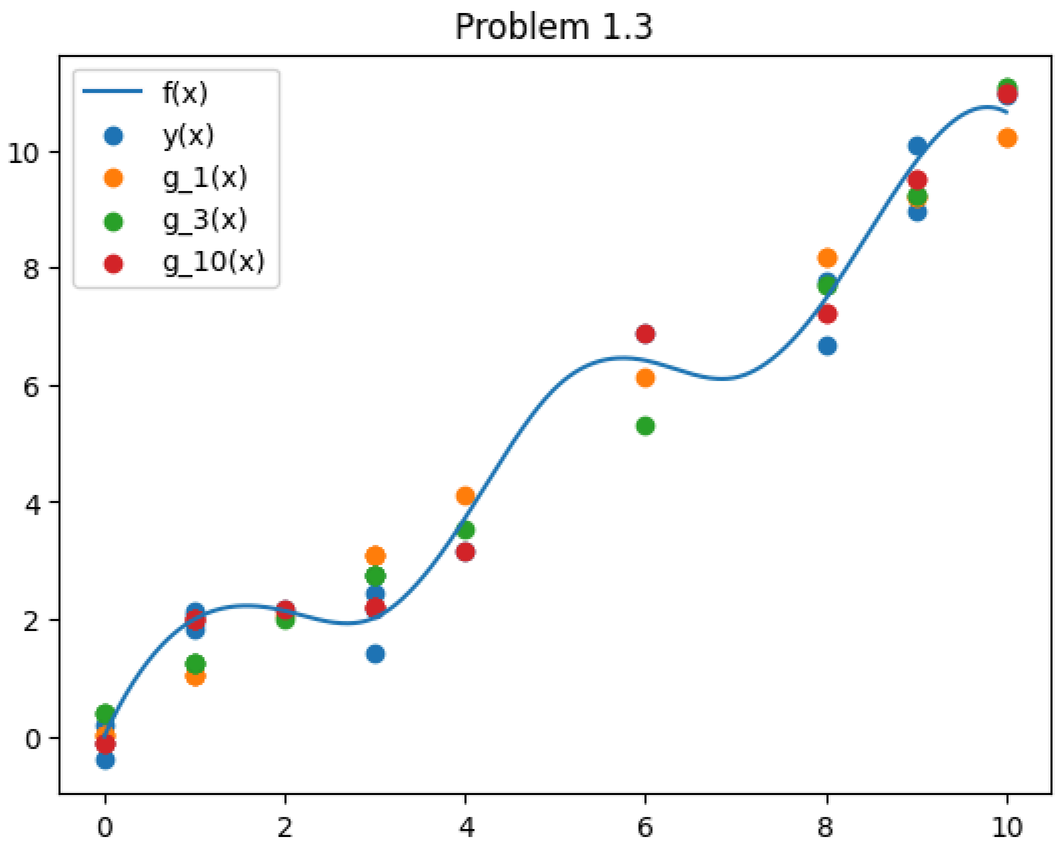
1.3

$g_n(x) = B_0 + B_1 x + B_2 x^2 + \ldots + B_n x^n$

In [2]:
```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
```

```python
x_train = dataset[["x"]]
y_train = dataset["y"].values
f_train = dataset["f(x)"].values

# fit estimators
model_poly_1 = LinearRegression().fit(x_train, y_train)
dataset["g_1"] = model_poly_1.predict(x_train)
print(f"Model g_1 intercept: {model_poly_1.intercept_}")
print(f"Model g_1 coeefficients: {model_poly_1.coef_}")

x_train_poly_3 = PolynomialFeatures(degree=3).fit_transform(x_train)
model_poly_3 = LinearRegression().fit(x_train_poly_3, y_train)
dataset["g_3"] = model_poly_3.predict(x_train_poly_3)
print(f"Model g_3 intercept: {model_poly_3.intercept_}")
print(f"Model g_3 coeefficients: {model_poly_3.coef_}")

x_train_poly_10 = PolynomialFeatures(degree=10).fit_transform(x_train)
model_poly_10 = LinearRegression().fit(x_train_poly_10, y_train)
dataset["g_10"] = model_poly_10.predict(x_train_poly_10)
print(f"Model g_10 intercept: {model_poly_10.intercept_}")
print(f"Model g_10 coeefficients: {model_poly_10.coef_}")

# plot
X_1 = np.arange(XMAX + 1)
F_1 = [f_func(x) for x in X_1]
x_smooth = np.linspace(0, XMAX, 500)
smooth_func = interp1d(X_1, F_1, kind='cubic')
dataset.sort_values(["x"], inplace=True)

plt.title("Problem 1.3")
plt.plot(x_smooth, smooth_func(x_smooth), label="f(x)")
plt.scatter(dataset['x'], dataset['y'], label="y(x)")
plt.scatter(dataset['x'], dataset['g_1'], label="g_1(x)")
plt.scatter(dataset['x'], dataset['g_3'], label="g_3(x)")
plt.scatter(dataset['x'], dataset['g_10'], label="g_10(x)")
plt.legend()
plt.show()
```

```
Model g_1 intercept: 0.026180552877201002
Model g_1 coeefficients: [1.01859347]
Model g_3 intercept: 0.3929045262658426
Model g_3 coeefficients: [ 0.          0.89013749 -0.055449    0.00731094]
Model g_10 intercept: -0.10997356210055464
Model g_10 coeefficients: [ 0.00000000e+00  2.39270701e+00  5.71449973e-01 -
7.67018200e-01
 -5.73316016e-01  7.01805044e-01 -2.76610179e-01  5.62215600e-02
 -6.33669879e-03  3.75754822e-04 -9.14406761e-06]
```



Estimator g_1 is underfitting, and estimator g_{10} is overfitting.

1.4

$Bias^2 = \frac{1}{t}\sum_{i=1}^{t}(f(x_i) - \mathbb{E}[g(x_i)])^2$

The term $f(x_i)$ is the truth value at x_i

The Term expected value of the prediction $\mathbb{E}[g(x_i)]$ is the average of the prediction for x_i across all possible datasets

$Variance = \frac{1}{t}\mathbb{E}[\sum_{i=1}^{t}(\mathbb{E}[g(x_i)] - g(x_i))^2]$

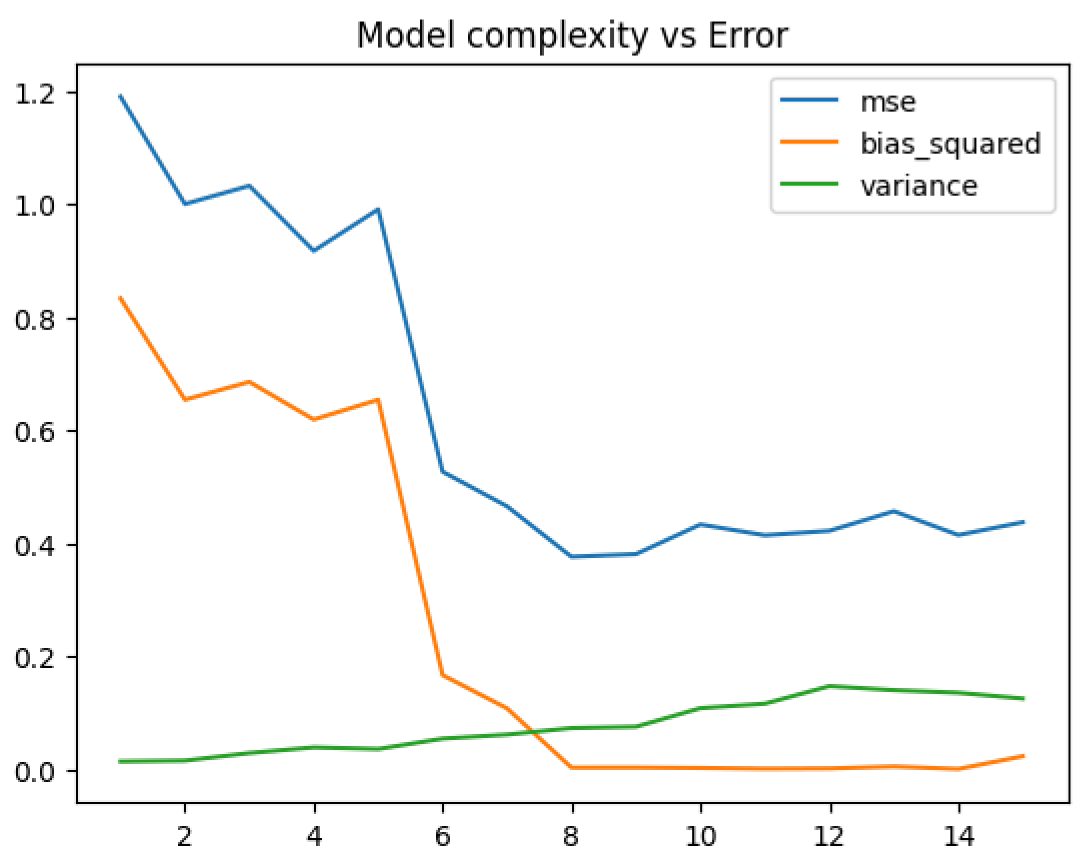
$\text{MSE} = \frac{1}{t}\sum_{i=1}^{t}(f(x_i) + \epsilon - g(x_i))^2$

In [3]:
```
from collections import defaultdict
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import Ridge

# config
MU = 0
SIGMA = math.sqrt(0.3)
N = 50 # dataset size
N_test = 10
N_train = 40
```

```
XMAX = 10
M = 100 # number of datasets
DEGREE = 15 # try polynomial regression up to degree DEGREE

random.seed(21)
np.random.seed(21)

x = np.linspace(0, XMAX, N)
x = np.random.permutation(x)
X_train = np.array(x[:N_train])
X_test = np.array(x[N_train:])

def simulate(degree, X_train, X_test, regularize=False):

    y_preds = []
    y_tests = []

    for _ in range(M):
        # Generate dataset
        y_train = np.array([y_func(x, MU, SIGMA) for x in X_train])
        y_test = np.array([y_func(x, MU, SIGMA) for x in X_test])

        # Transform dataset
        poly_transformer = PolynomialFeatures(degree=degree)
        X_train_poly = poly_transformer.fit_transform(np.expand_dims(X_trair
        X_test_poly = poly_transformer.transform(np.expand_dims(X_test, axis

        # Train
        if regularize:
            model = Ridge(alpha=0.5).fit(X_train_poly, y_train)
        else:
            model = LinearRegression().fit(X_train_poly, y_train)

        # Predict
        y_pred = model.predict(X_test_poly)
        y_preds.append(y_pred)
        y_tests.append(y_test)

    y_preds = np.stack(y_preds, axis=0)
    y_tests = np.stack(y_tests, axis=0)
    f = np.array([f_func(x) for x in X_test])

    # compute MSE
    mse = mean_squared_error(y_tests, y_preds)

    # compute bias-squared
    exp_preds = np.mean(y_preds, axis=0)

    bias_squared = np.mean(np.square(f - exp_preds))
    variance = np.mean(np.mean(np.square(exp_preds - y_preds), axis=0))
    computed_noise = mse - (bias_squared + variance)

    return {
        "mse": float(mse),
        "bias_squared": float(bias_squared),
        "variance": float(variance),
```

```
        "computed_noise": float(computed_noise),
    }


results_map = {}

for d in range(1, DEGREE + 1):
    results_map[f"g_{d}"] = simulate(d, X_train, X_test)

results_df = pd.DataFrame(results_map)
display(results_df)
complexity = np.arange(1, 16)

# plot
plt.title("Model complexity vs Error")
plt.plot(complexity, results_df.T["mse"].values, label="mse")
plt.plot(complexity, results_df.T["bias_squared"].values, label="bias_square
plt.plot(complexity, results_df.T["variance"].values, label="variance")
plt.legend()
plt.show()
```

	g_1	g_2	g_3	g_4	g_5	g_6	g_
mse	1.190326	1.000286	1.032534	0.917501	0.990884	0.526866	0.46559
bias_squared	0.833505	0.654311	0.685812	0.619258	0.654237	0.166760	0.10789
variance	0.013945	0.015273	0.028701	0.038775	0.035863	0.054237	0.06135
computed_noise	0.342875	0.330703	0.318021	0.259469	0.300784	0.305870	0.29635



The Best model has a polynomial degree of 8, where it has the lowest MSE and the optimal balance between bias_squared and variance.

1.5 Regularization

In [5]:
```
import warnings
warnings.filterwarnings("ignore")

results_map = {}

results_map[f"g_10"] = simulate(10, X_train, X_test, False)
results_map[f"g_10_L2"] = simulate(10, X_train, X_test, True)

results_df = pd.DataFrame(results_map)
results_df
```

Out[5]:

	g_10	g_10_L2
mse	0.408168	0.376128
bias_squared	0.001975	0.015525
variance	0.090800	0.077387
computed_noise	0.315392	0.283216

Going from the unregularized order 10 polynomial model to regularized model,

1. MSE decreased slightly
2. $Bias^2$ increased
3. Variance decreased

Therefore, the regularized model has a higher bias, lower variance, and lower MSE.

This is because the regularized model penalized complex model with larger coefficients, so that the model doesn't fit too closely to the data. This leads to better generalization to unseen data. Thus, it results in lower MSE on testing dataset. Bias increased because regularization simplified the model, and variance decreased because it limited the model's complexity.

Problem 2 - Precision, Recall, ROC

2.1

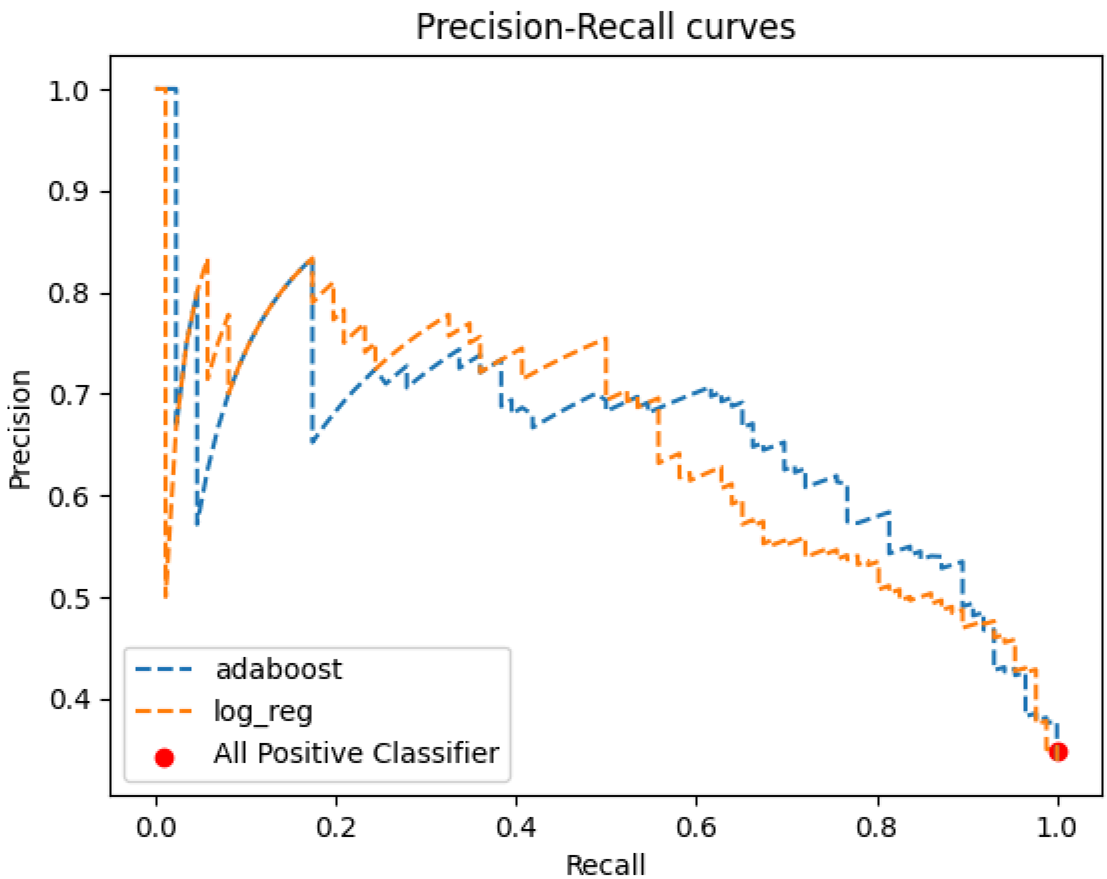
Q: Does true negative matter for both ROC and PR curve? Argue why each point on ROC curve corresponds to an unique point on PR curve.

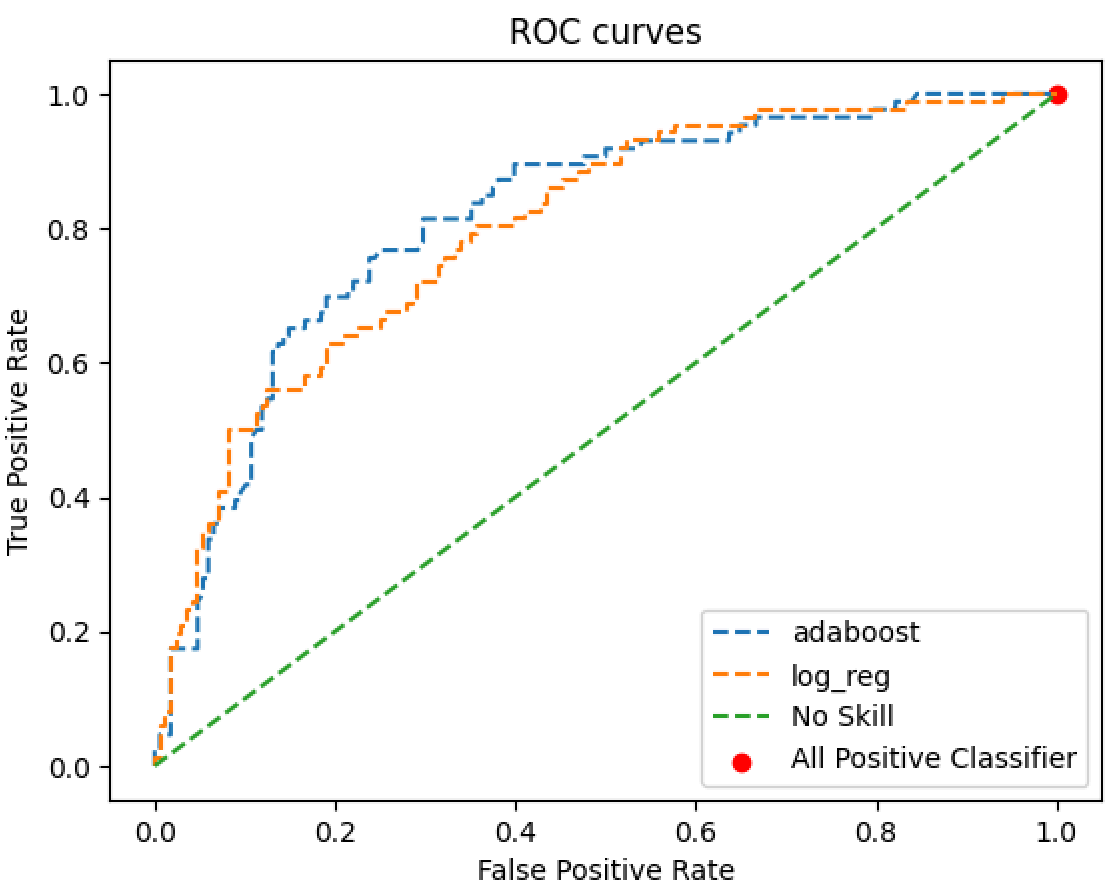
A: True negative is important in the calculation of false positive rate (FPR), which is the x-axis of the ROC curve. However, true negative does not matter for PR curve since precision and recall metrics don't use true negative in their calculation. Each point on ROC curve corresponds to an unqiue point on PR curve because both corresponding points depend on the same set of predictions at a certain threshold. These predictions at a certain threshold form a specific confusion matrix, which consists of TP, TN, FP, FN that are directly used to calculate precision, recall, false positive rate, and true positive rate. Precision and recalls are used to plot PR curve, and FPR and TPR are used to plot ROC curve.

2.2

In [6]:
```
from scipy.io import arff
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.ensemble import AdaBoostClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_curve, precision_recall_curve
from sklearn.metrics import PrecisionRecallDisplay
from sklearn.metrics import auc
from sklearn.metrics._ranking import _binary_clf_curve

# load data
arff_file = arff.loadarff('dataset_37_diabetes.arff')
prob2_2_data = pd.DataFrame(arff_file[0])
prob2_2_data['class'] = prob2_2_data['class'].map({b"tested_positive": 1, b"
X = prob2_2_data[[col for col in prob2_2_data.columns if col != 'class']]
y = prob2_2_data['class'].values

# split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, ra

def make_pipe(model_name, model):
    return Pipeline([("scaler", StandardScaler()), (model_name, model)])

results_map = {}
models = [
    ("adaboost", AdaBoostClassifier(n_estimators=100, algorithm="SAMME", ran
    ("log_reg", LogisticRegression()),
]

for model_name, model in models:
    pipe = make_pipe(model_name, model)
    pipe.fit(X_train, y_train)
    y_pred = pipe.predict_proba(X_test)[:, 1]
    fpr, tpr, thresholds_roc = roc_curve(y_test, y_pred)
    precision, recall, thresholds_pr = precision_recall_curve(y_test, y_pred
    auroc = auc(fpr, tpr)
    aupr = auc(recall, precision)
    pi = 268/768 # proportion of positives in dataset
    recallG = [float((r - pi) / ((1-pi)*r + 0.0001)) for r in recall]
    precisionG = [float((p - pi) / ((1-pi)*p + 0.0001)) for p in precision]
    auprg = auc(recallG, precisionG)
    results_map[model_name] = {
```

```
        "fpr": fpr,
        "tpr": tpr,
        "precision": precision,
        "recall": recall,
        "thresholds_pr": thresholds_pr,
        "thresholds_roc": thresholds_roc,
        "auroc": auroc,
        "aupr": aupr,
        "auprg": auprg,
    }

plt.title("Precision-Recall curves")
plt.plot(results_map["adaboost"]["recall"], results_map["adaboost"]["precisi
plt.plot(results_map["log_reg"]["recall"], results_map["log_reg"]["precision
plt.scatter([1], [pi], label="All Positive Classifier", color="red")
plt.ylabel("Precision")
plt.xlabel("Recall")
plt.legend(loc="lower left")
plt.show()

plt.title("ROC curves")
plt.plot(results_map["adaboost"]["fpr"], results_map["adaboost"]["tpr"], '--
plt.plot(results_map["log_reg"]["fpr"], results_map["log_reg"]["tpr"], '--',
plt.plot(np.linspace(0, 1, 100), np.linspace(0, 1, 100), '--', label="No Ski
plt.scatter([1], [1], label="All Positive Classifier", color="red")
plt.ylabel("True Positive Rate")
plt.xlabel("False Positive Rate")
plt.legend()
plt.show()
```





Note: For all positive classifier, we have

TPR = 1; FPR = 1; Precision = $\frac{P}{(P+N)} = \frac{268}{768}$; Recall = 1

2.3 PR gain curve

In [7]:
```
print(f"AUROC for adaboost {results_map["adaboost"]["auroc"]}")
print(f"AUPR for adaboost {results_map["adaboost"]["aupr"]}")
print(f"AUPRG for adaboost {results_map["adaboost"]["auprg"]}")

print(f"AUROC for logistic regression {results_map["log_reg"]["auroc"]}")
print(f"AUPR for logistic regression {results_map["log_reg"]["aupr"]}")
print(f"AUPRG for logistic regression {results_map["log_reg"]["auprg"]}")
```

```
AUROC for adaboost 0.8160991140642303
AUPR for adaboost 0.6583825843463507
AUPRG for adaboost 3484.9656016837307
AUROC for logistic regression 0.7994878183831672
AUPR for logistic regression 0.6522517882377267
AUPRG for logistic regression 3476.754018649303
```

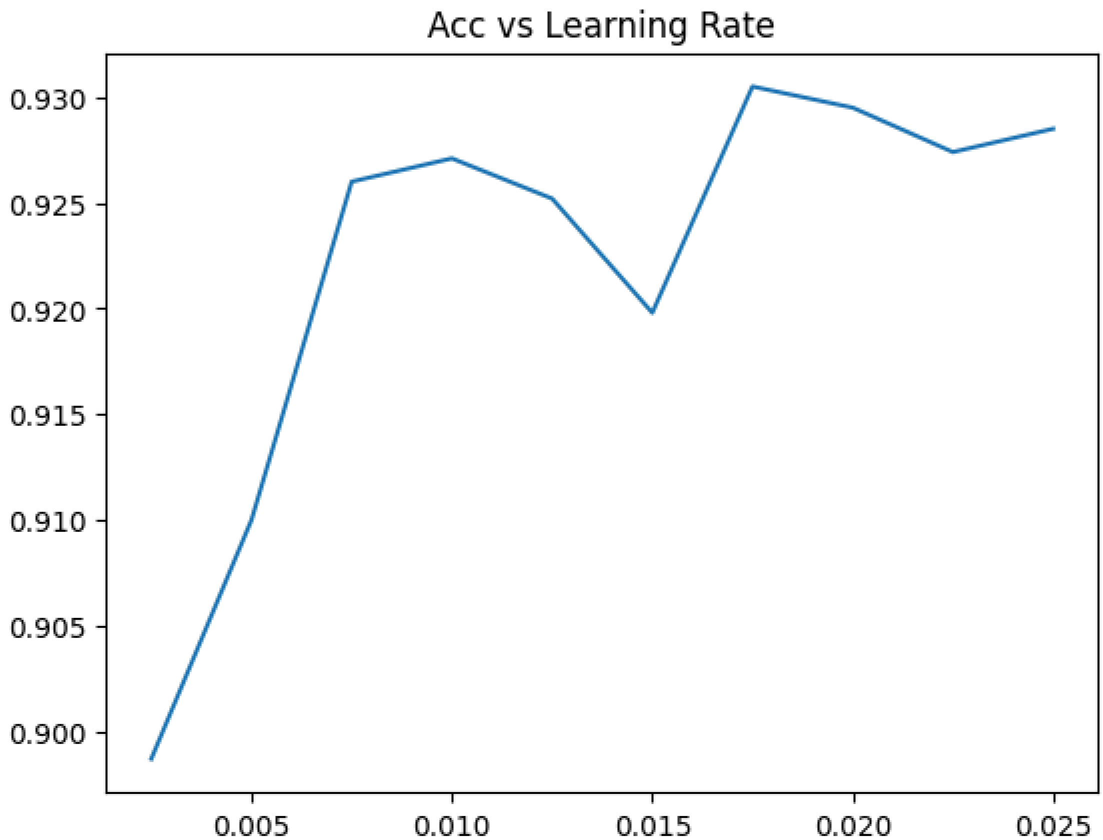
I disagree that PR gain curves should be used over PR curves. There could be unstable values that fall into the negative range when calculating the precision gain and recall gain values. In that case, my AUPRG value ends up becoming larger than 1.

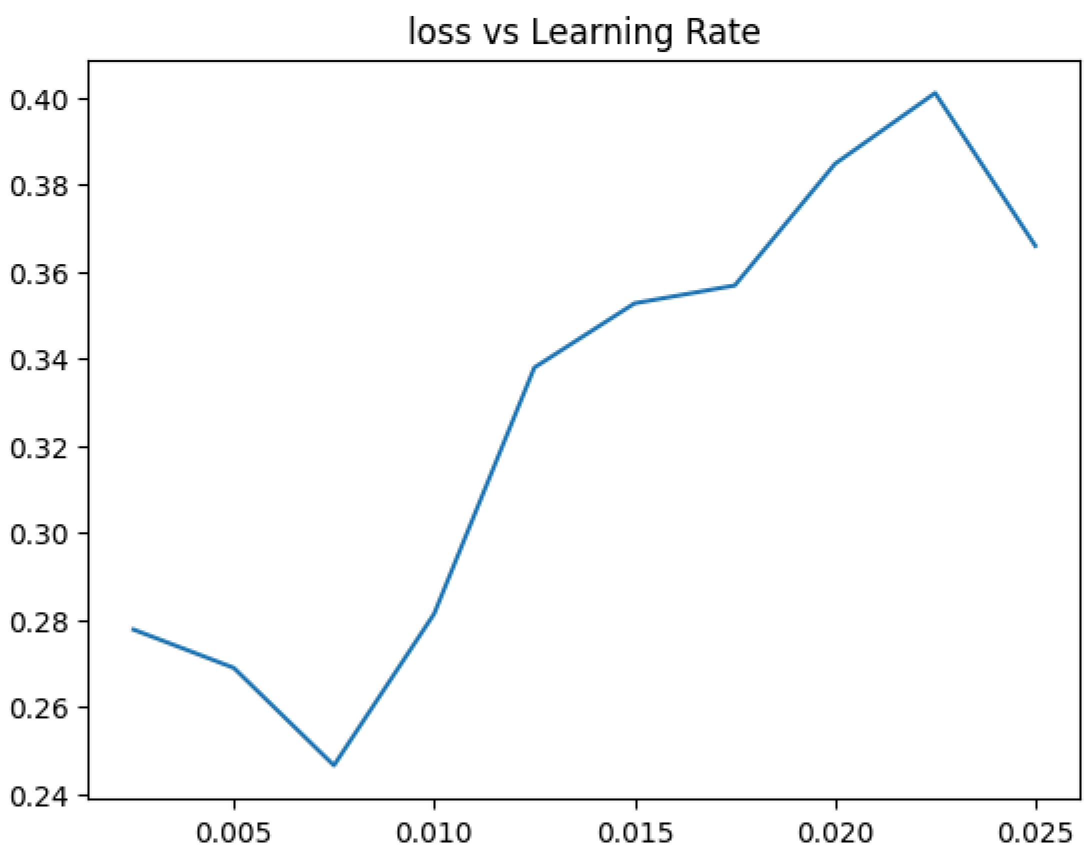
Problem 3 - Learning Rate, Batch Size, FashionMNIST

3.1

In [8]:
```
import json

with open("prob3_1_results_1.json", "r") as f:
    prob3_1_results = json.load(f)


lrs = []
accs = []
losses = []
for i, results in prob3_1_results.items():
    lrs.append(results["lr"])
    accs.append(results["val_acc"][-1])
    losses.append(results["val_loss"][-1])

prob3_1_results_df = pd.DataFrame({"lr": lrs, "acc": accs, "loss": losses})
prob3_1_results_df.sort_values(["lr"], inplace=True)


plt.title("Acc vs Learning Rate")
plt.plot(prob3_1_results_df["lr"], prob3_1_results_df["acc"])
plt.show()

plt.title("loss vs Learning Rate")
```

```python
plt.plot(prob3_1_results_df["lr"], prob3_1_results_df["loss"])
plt.show()
```



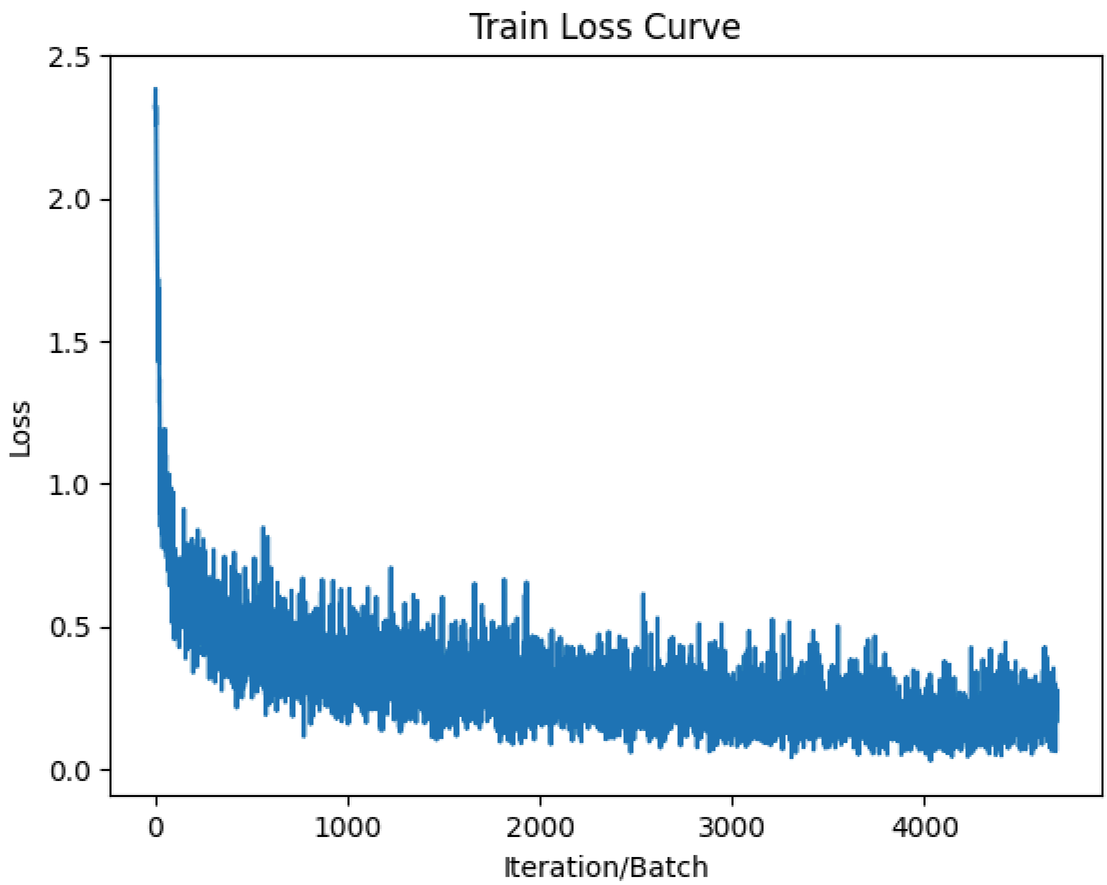


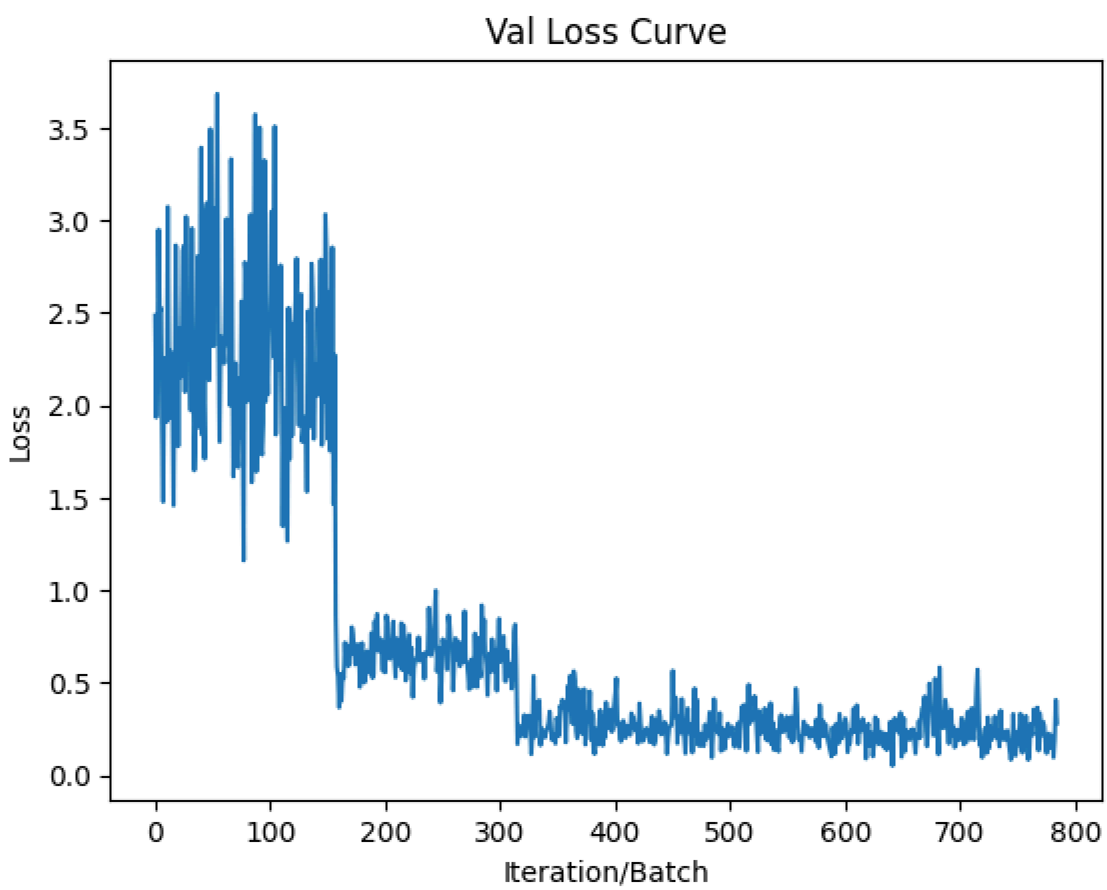
lr_{min} = 0.0025

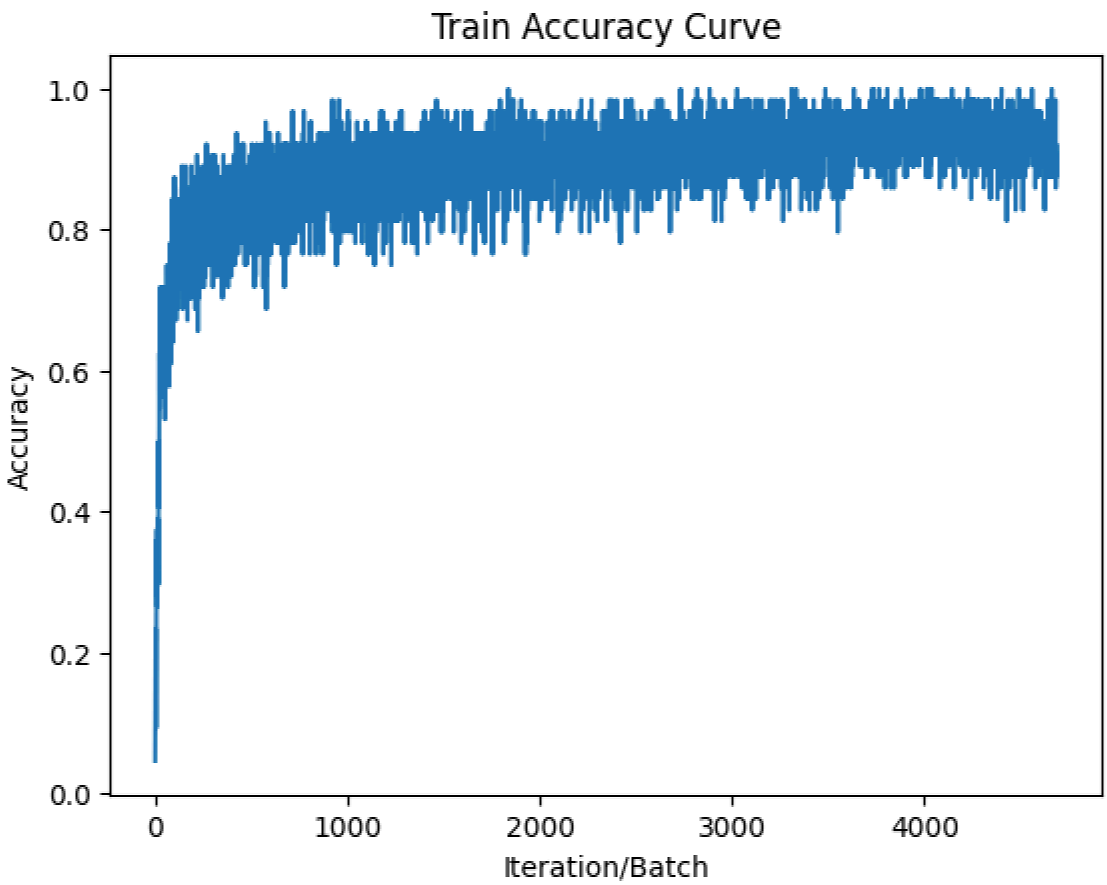
lr_{max} = 0.01

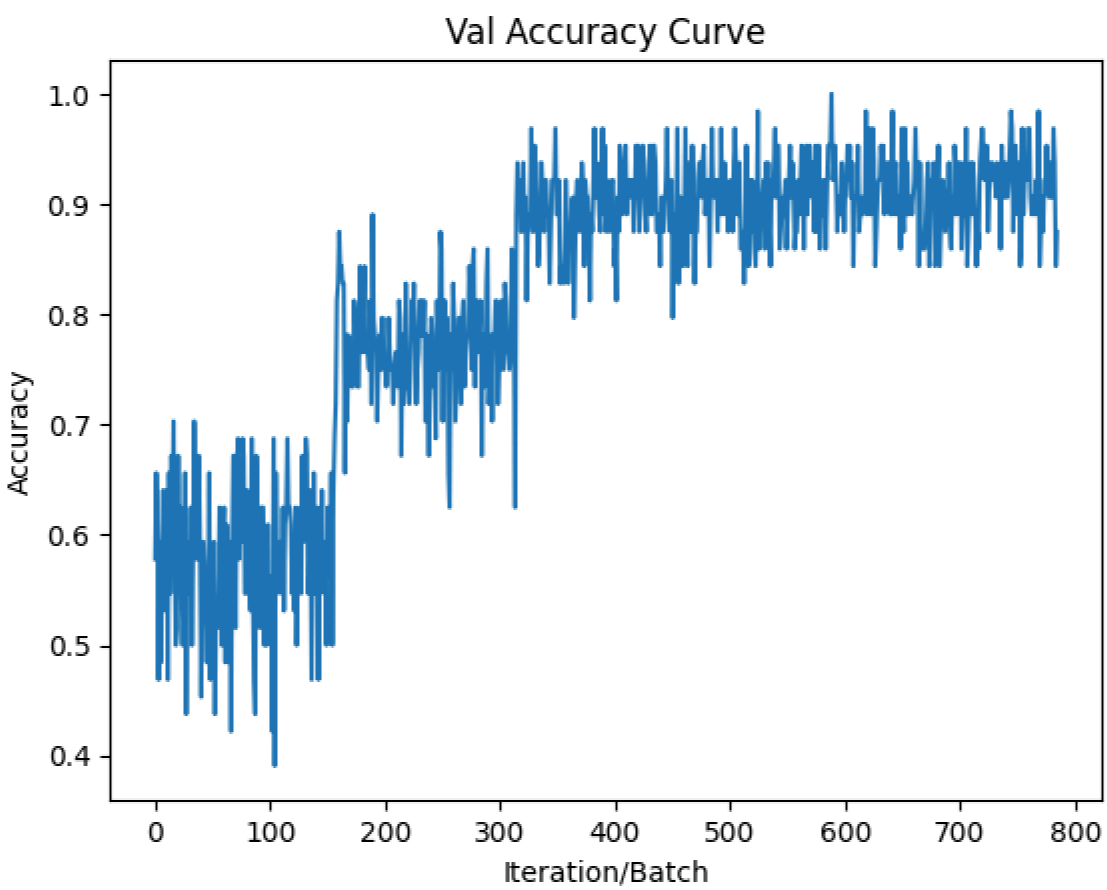
3.2

In [9]:
```
with open("prob3_2_results_1.json", "r") as f:
    prob3_2_results = json.load(f)

num_iteration_train = np.arange(len(prob3_2_results["train_batch_losses"]))
num_iteration_val = np.arange(len(prob3_2_results["val_batch_losses"]))

plt.title("Train Loss Curve")
plt.plot(num_iteration_train, prob3_2_results["train_batch_losses"])
plt.xlabel("Iteration/Batch")
plt.ylabel("Loss")
plt.show()

plt.title("Val Loss Curve")
plt.plot(num_iteration_val, prob3_2_results["val_batch_losses"])
plt.xlabel("Iteration/Batch")
plt.ylabel("Loss")
plt.show()



plt.title("Train Accuracy Curve")
plt.plot(num_iteration_train, prob3_2_results["train_batch_accs"])
plt.xlabel("Iteration/Batch")
plt.ylabel("Accuracy")
plt.show()


plt.title("Val Accuracy Curve")
plt.plot(num_iteration_val, prob3_2_results["val_batch_accs"])
plt.xlabel("Iteration/Batch")
plt.ylabel("Accuracy")
plt.show()
```


Train Loss Curve
Loss
Iteration/Batch
2.5
2.0
1.5
1.0
0.5
0.0
0
1000
2000
3000
4000


Val Loss Curve
Loss
Iteration/Batch
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
100
200
300
400
500
600
700
800


Train Accuracy Curve
1.0
0.8
0.6
0.4
0.2
0.0
Accuracy
0
1000
2000
3000
4000
Iteration/Batch


Val Accuracy Curve
1.0
0.9
0.8
0.7
0.6
0.5
0.4
Accuracy
0
100
200
300
400
500
600
700
800
Iteration/Batch

3.3

In [10]:
```
with open("prob3_3_results.json", "r") as f:
    prob3_3_results = json.load(f)

train_losses = prob3_3_results["train_loss"]
batch_size = 32
batch_sizes = []
while batch_size <= 8192:
    batch_sizes.append(batch_size)
    batch_size *= 2

# each epoch uses one batch_size
# epoch0: 32
# epoch1: 64
# ...
plt.title("Training Loss vs Batch size")
plt.plot(batch_sizes, train_losses)
plt.xlabel("Batch Size")
plt.ylabel("Loss")
plt.show()
```

The final model from problem 3.3 as shown in the plot above is similar to the Training Loss curve shown in the plot in Problem 3.2 with cyclical learning rate policy. They both show similar steep downward trend.

Problem 4 - Convolutional Neural Networks Architectures

4.1

Table 1. VGG19 Activation units and paramteters calculation

Layer	Number of Activations (Memory)	parameters (Compute)
Input	224 * 224 * 3 = 150K	0
Conv3-64	224 * 224 * 64 = 3.2M	(3 * 3 * 3) * 64 = 1,728
Conv3-64	224 * 224 * 64 = 3.2M	(3 * 3 * 64) * 64 = 36,864
Pool2	112 * 112 * 64 = 800K	0
Conv3-128	112 * 112 * 128 = 1.6M	(3 * 3 * 64) * 128 = 73,728
Conv3-128	112 * 112 * 128 = 1.6M	(3 * 3 * 128) * 128 = 147,456
Pool2	56 * 56 * 128 = 400K	0
Conv3-256	56 * 56 * 256 = 800K	(3 * 3 * 128) * 256 = 294,912
Conv3-256	56 * 56 * 256 = 800K	(3 * 3 * 256) * 256 = 589,824
Conv3-256	56 * 56 * 256 = 800K	(3 * 3 * 256) * 256 = 589,824
Conv3-256	56 * 56 * 256 = 800K	(3 * 3 * 256) * 256 = 589,824
Pool2	28 * 28 * 256 = 200K	0
Conv3-512	28 * 28 * 512 = 400K	(3 * 3 * 256) * 512 = 1,179,648
Conv3-512	28 * 28 * 512 = 400K	(3 * 3 * 512) * 512 = 2,359,296
Conv3-512	28 * 28 * 512 = 400K	(3 * 3 * 512) * 512 = 2,359,296
Conv3-512	28 * 28 * 512 = 400K	(3 * 3 * 512) * 512 = 2,359,296
Pool2	14 * 14 * 512 = 100K	0
Conv3-512	14 * 14 * 512 = 100K	(3 * 3 * 512) * 512 = 2,359,296
Conv3-512	14 * 14 * 512 = 100K	(3 * 3 * 512) * 512 = 2,359,296
Conv3-512	14 * 14 * 512 = 100K	(3 * 3 * 512) * 512 = 2,359,296
Conv3-512	14 * 14 * 512 = 100K	(3 * 3 * 512) * 512 = 2,359,296
Pool2	7 * 7 * 512 = 25K	0
FC	4096	(7 * 7 * 512) * 4096 = 102,760,448
FC	4096	4096 * 4096 = 16,777,216
FC	1000	4096 * 1000 = 4,096,000
TOTAL	16.5M	143,652,544

4.2

(a) According to the Googlenet paper, the general idea behind designing an inception module in a CNN is based on finding out how an optimal local sparse structure in a convolutional vision network can be approximated and covered by readily available dense components.

(b) Calcuate output sizes

Naive version:

Concatenate (32 x 32 x 128) + (32 x 32 x 192) + (32 x 32 x 96) + (32 x 32 x 256) at the channel/filter dimension => (32 x 32 x 672)

Dimension reductions version:

Concatenate 128 + 192 + 96 + 64 => (32 x 32 x 480)

(c) Calculate number of convolutional operations

Naive version:

(1 * 1 * 256 * 128) + (3 * 3 * 256 * 192) + (5 * 5 * 256 * 96) + 0

= 32768 + 442368 + 614400

= 1,089,536

Dimension reductions version:

(1 * 1 * 256 * 128) + (1 * 1 * 256 * 128) + (3 * 3 * 128 * 192) + (1 * 1 * 256 * 32) + (5 * 5 * 32 * 96) + 0 + (1 * 1 * 256 * 64)

= 388,096

(d) How dimension reductions technique helps?

The inception module with dimension reductions technique is significantly faster than the naive architecture with much lower computational steps. The number of convolutional computation decreased from 1,089,536 to 388,096, which is a 701,440 operations reduction or 64.4% decrease.

Problem 5

Staleness at the start of the compute of the following gradients:

$g[L_1, 1] = 0$

$g[L_1, 2] = 0$

$g[L_1, 3] = 1$

$g[L_1, 4] = 0$

$g[L_2, 1] = 2$

$g[L_2, 2] = 0$ (Since PS receives gradients and updates weights from $g[L_1, 4]$ and $g[L_2, 1]$ at the same time at second 5. The gradients read at the beginning of the compute of $g[L_2, 2]$ is not stale)