

# Midterm 1 Prep

CPSC 330 Tutorial 4

# Introduction to Machine Learning

Which of the following problems is **most suitable** for machine learning?

- A) Computing the sum of two numbers
- B) Predicting housing prices based on historical data
- C) Sorting a list of numbers
- D) Checking if a number is prime

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# Introduction to Machine Learning

Unsupervised learning would be more useful for:

- A) Predicting stock prices
- B) Classifying spam emails
- C) Identifying types of customers of an online retail store
- D) Diagnosing diseases

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Which of the following is an example of a **regression** problem?

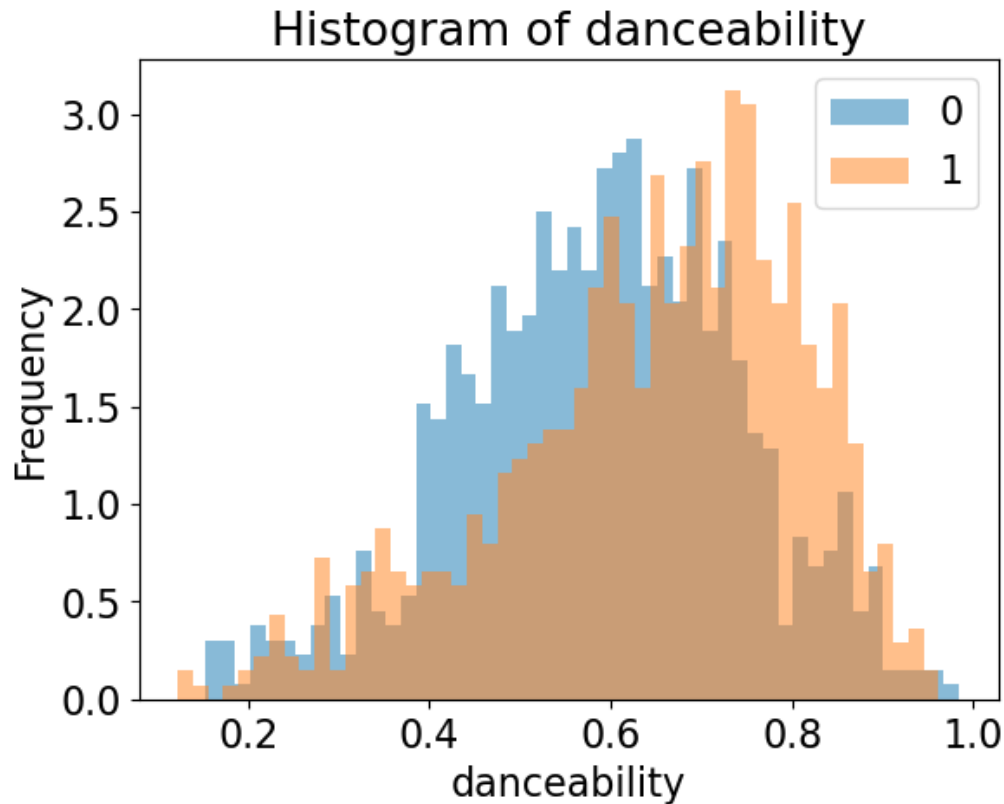
- A) Identifying if an email is spam or not
- B) Predicting tomorrow's temperature in degrees
- C) Classifying different species of flowers
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# EDA



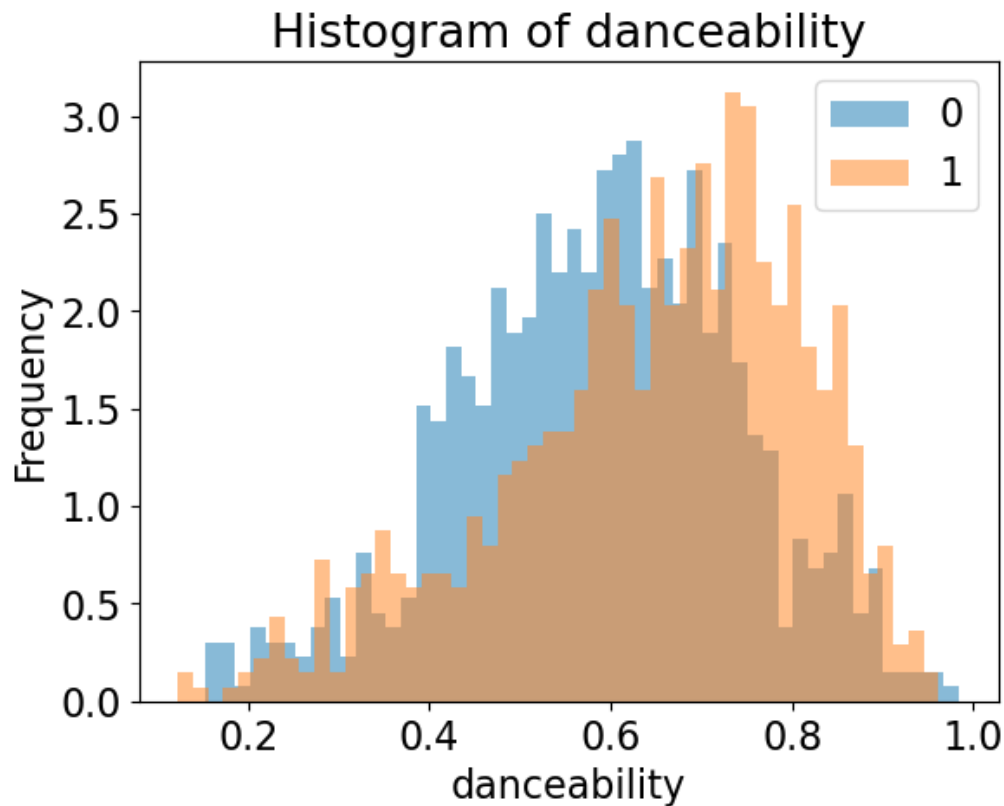
0 = not liked song; 1 = liked song

Based on this histogram, danceability is not a very good discriminant to separate the two classes. Should I remove it from my model?

- A. Yes, because it is not informative
- B. Yes, because its range is too narrow
- C. No, because the classes shows different frequencies across the range
- D. No, because it could be informative when combined with other features



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# Decision trees

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- B) Increase the risk of overfitting
- C) Increase model complexity
- D) Make the model more interpretable

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# K-Nearest Neighbors

What is a key **limitation** of k-Nearest Neighbors (kNN)?

- A) It requires labeled data
- B) It does not work for regression tasks
- C) It is computationally expensive for large datasets
- D) It cannot handle numerical features

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# K-Nearest Neighbors

All of the following will make a kNN classifier slower at generating predictions, but which one will have the smaller impact?

- A. A higher number of features
- B. A higher number of training samples
- C. A higher value of  $k$
- D. Using a distance metric that is computationally expensive (e.g., Mahalanobis distance instead of Euclidean)

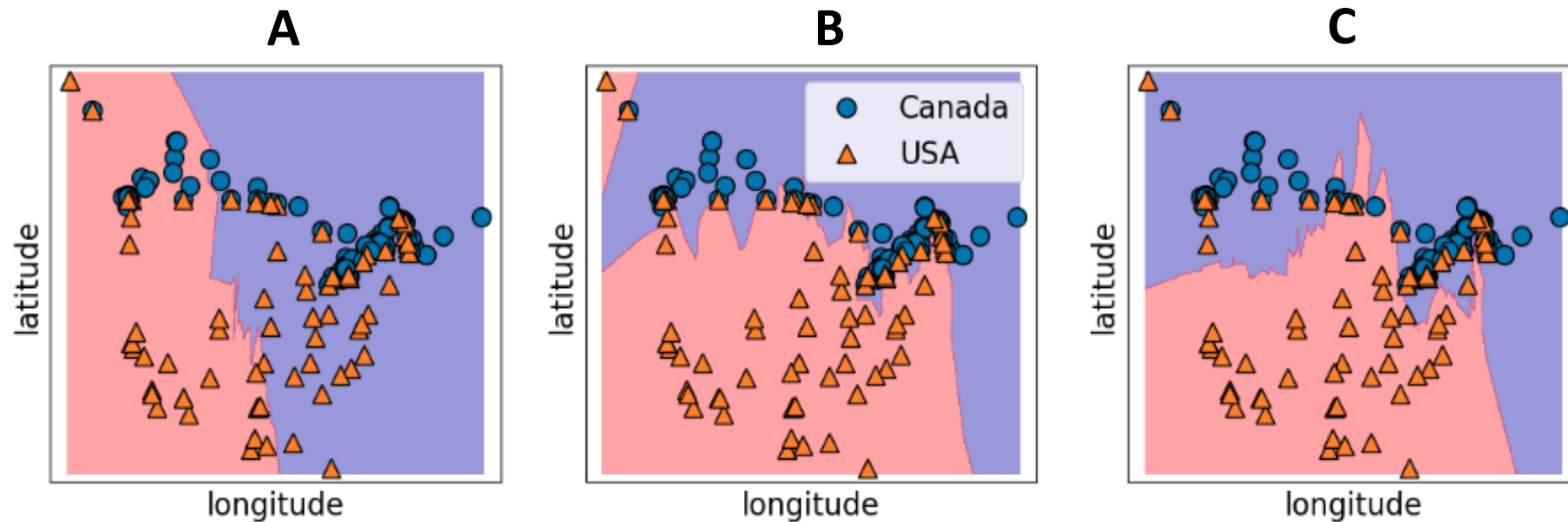
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# Decision boundaries

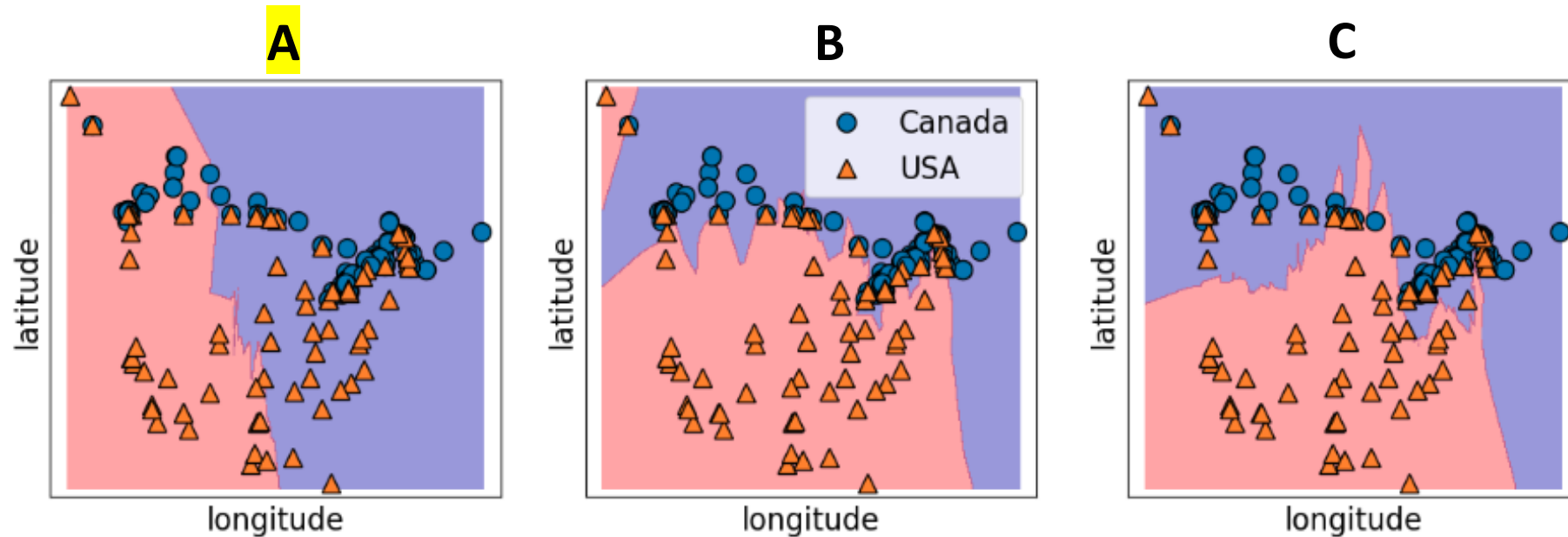
The following decision boundaries correspond to kNN classifiers trained with different values of  $k$ . Which one do you think was trained with the **highest** value of  $k$ ?





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# Underfitting/overfitting

What should I do to help prevent **overfitting**?

- A) Increase the number of features
- B) Reduce the amount of training data
- C) Use regularization techniques, like Ridge
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# Underfitting/overfitting

Which of the following scenarios suggests a model is suffering from **high bias**?

- A) The training and test errors are both high and similar in magnitude
- B) The training error is low, but the test error is significantly higher
- C) The model performs well on the training set but struggles with new data
- D) The model's performance improves significantly when adding more features

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# Cross validation

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# Preprocessing

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- B) Removing duplicate labels
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# Preprocessing

Sophia is a data scientist working on a **sentiment analysis model** for customer reviews. She decides to use **CountVectorizer** from scikit-learn to convert text into numerical features.

After applying **CountVectorizer** to her dataset, she notices something odd:

- The feature matrix has **many columns**, making it very sparse.
- Common words like "**the**," "**and**," "**is**" appear frequently, inflating the feature counts.
- Words like "**awesome**" and "**terrible**", which are important for sentiment analysis, are **overshadowed** by common words.

Her colleague suggests tweaking **CountVectorizer's parameters** to improve the feature representation. Which of the following would be the **best approach**?

- A) Set `stop_words='english'` to remove common words that don't add meaning to the sentiment.
- B) Set `max_features=10` to drastically reduce the vocabulary size.
- C) Use `binary=True` so that word frequency is ignored completely.
- D) Remove **low-frequency words** by setting `min_df=10` to filter out rare words.

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# Hyperparameters tuning

Given an SVM with an **RBF kernel**, increasing the gamma parameter will likely:

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- B) Reduce model complexity
- C) Make the model more sensitive to individual data points
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Compared to **Grid Search**, what is a key advantage of **Randomized Search**?

- A) It guarantees finding the best hyperparameters
- B) It reduces computational cost by sampling fewer hyperparameter combinations
- C) It always improves model accuracy
- D) It is also applicable to regression problems

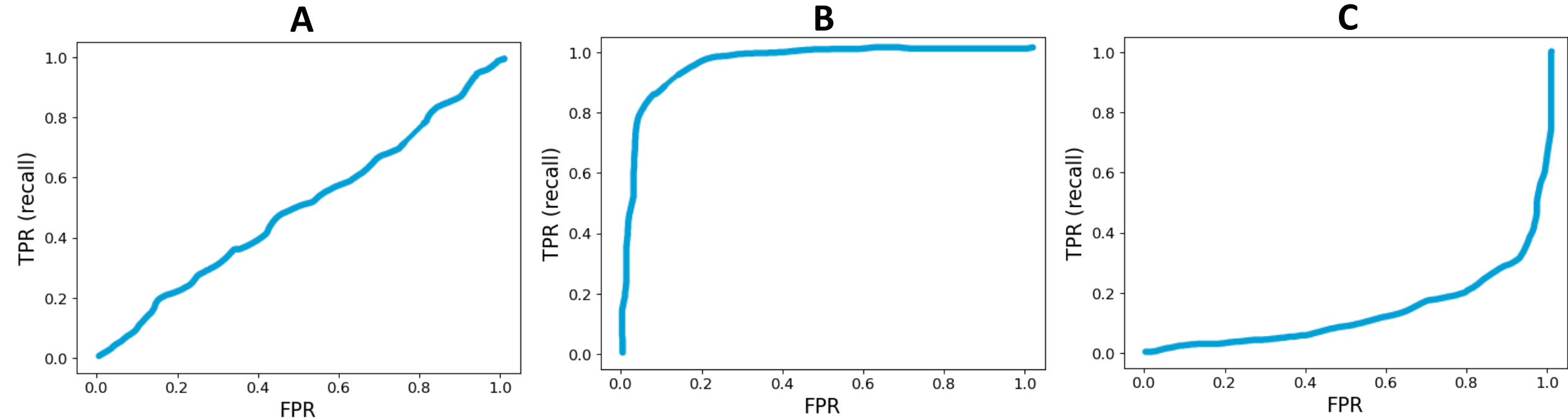
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# Classification metrics

I am tasked to solve a binary classification problem, but I am lazy and I decide to use a coin toss to assign each sample to a class (head = positive, tail = negative). The classes in the dataset are balanced. What ROC curve better corresponds to my approach?

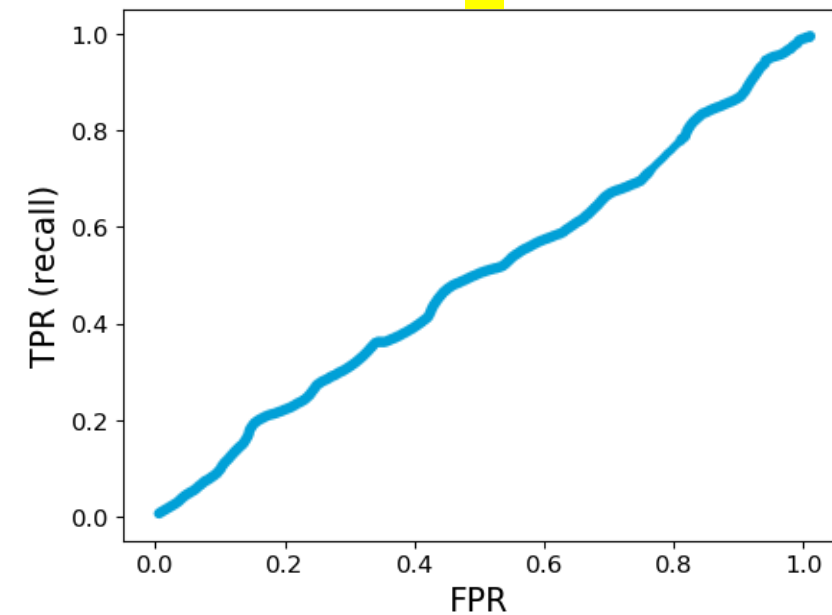




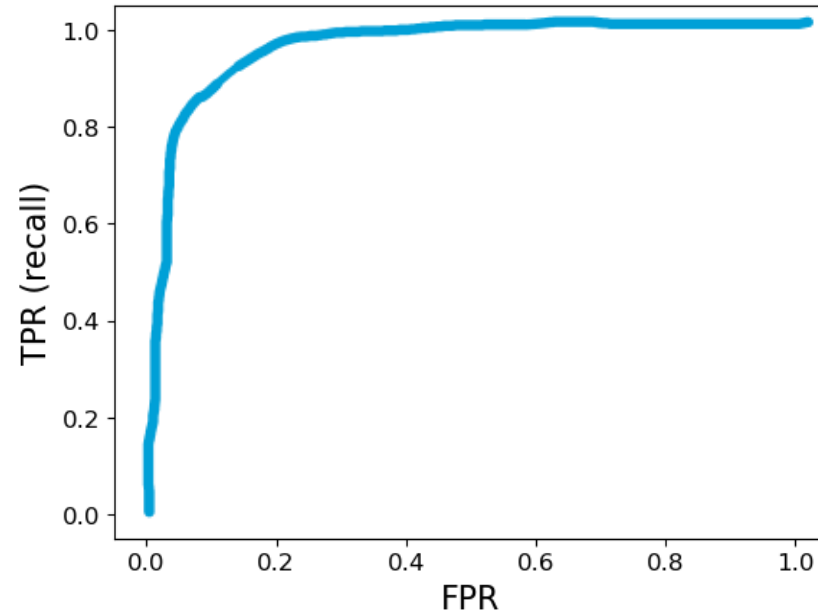
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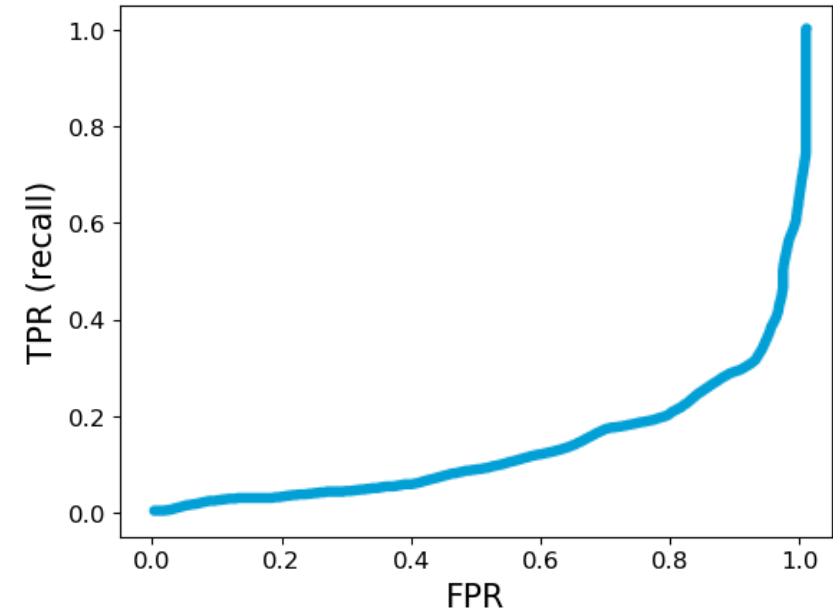
**A**



**B**



**C**



# Classification metrics

If a classification model achieves **100% recall**, what can we conclude?

- A) The model also has 100% accuracy
- B) The model correctly identified all positive samples but may have false positives
- C) The model does not make false positive predictions
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# Regression metrics

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1	0.001790	0.000803	-0.001266	0.0
2	0.001433	0.000520	-0.011767	0.0
3	0.002221	0.000332	-0.006744	0.0
4	0.001894	0.000433	-0.076533	0.0
5	0.004854	0.001406	-0.003133	0.0
6	0.002746	0.001011	-0.000397	0.0
7	0.004143	0.001566	-0.003785	0.0
8	0.000652	0.000221	-0.001740	0.0
9	0.000713	0.000226	-0.000117	0.0

The table on the left shows the cross-validation results for a regression problem. Which regressor is likely being used here?

- A. `DummyRegressor(strategy="median")`
- B. `SVR(kernel='rbf')`
- C. `DummyRegressor(strategy="mean")`
- D. `SVR(kernel='linear')`

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Liam is a financial analyst at a startup that predicts **monthly revenue** for different business units. He is evaluating the model's performance and has to choose between using **Mean Absolute Percentage Error (MAPE)** and  **$R^2$  (coefficient of determination)**.

Liam notices something interesting:

- The model performs **well** for high-revenue business units but **poorly** for smaller ones.
- The  **$R^2$  score is high (0.92)**, but the **MAPE is 40%**, meaning predictions are off by an average of 40% of actual revenue.
- Some business units have **low actual revenue**.

Which metric should Liam trust more in this case, and why?

**A)** MAPE is better because it considers percentage errors, making it fair across different revenue sizes.

**B)**  $R^2$  is better because a high value (0.92) means the model explains most of the variance; Liam should use  $R^2$  and ignore MAPE.

**C)**  $R^2$  is always the best metric for regression, regardless of data characteristics.

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# GL on Midterm 1! :)

