Week8: Model Training

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COURSE: IS597MLC-SU2024

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Outline

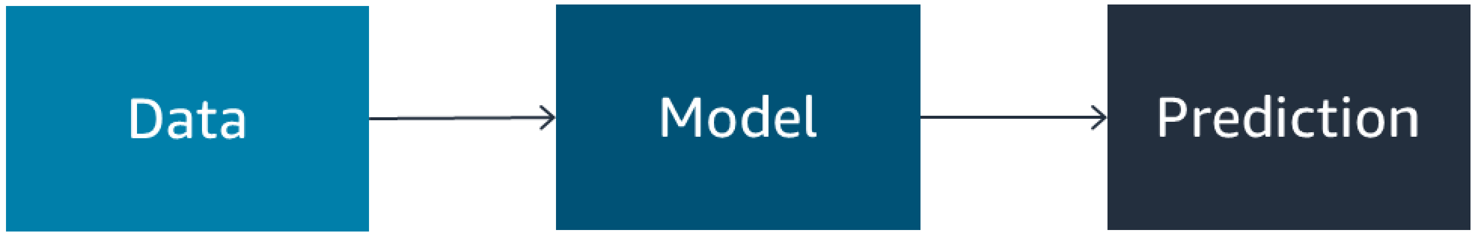
- ML workflow review
- Transforming data
- Model training
- Performance evaluation

Part 1

Machine Learning Workflow Review

Simplified ML Steps

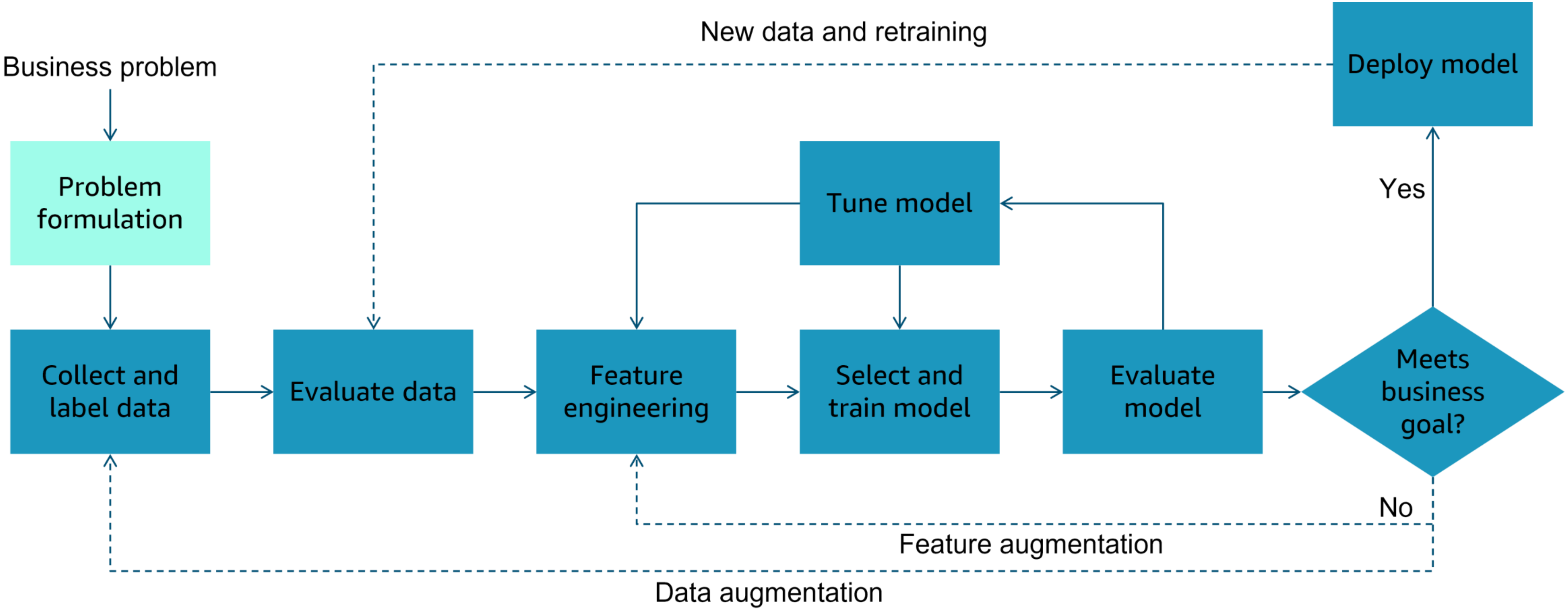
Machine Learning focuses on ***using data*** to ***train ML models*** so these models can ***make predictions***.



Machine learning flow

Source: Amazon Web Services

Machine Learning Workflow



Source: Amazon Web Services

Types of ML Learning

- **Supervised**: Classification, Regression
- Unsupervised: Clustering
- Reinforcement: Neural Networks

Source: Amazon Web Services

Part 2
Transforming Data

Supervised ML: Labeled Data

ML problems need a lot of data - also called **instances (observations) -** where the target answer or prediction is **already known.**

Customer	Date of transaction	Vendor	Charge amount	Was this fraud?
ABC	10/5	Store 1	10.99	No
DEF	10/5	Store 2	99.99	Yes
GHI	10/5	Store 2	15.00	No
JKL	10/6	Store 2	99.99	?
MNO	10/6	Store 1	99.99	Yes

Feature

Target

Source: Amazon Web Services

Text Vectorization

- Transform textual data into numerical representations
- Enables machines to process and extract meaning
- Techniques:
  - Bag-of-Words
  - TF-IDF (Term Frequency * Inver Document Frequency)
  - Word Embeddings (e.g., Word2Vec, GloVe, etc.)
- Determine the features (e.g., words) that you will use in the classifier
- Select the best words that will play a critical role in classification performance
- Reducing the vocabulary size helps to ensure that the classifier has the best chance of finding non-spurious associations

TF-IDF

- A statistical measure that evaluates how relevant a word is to a document in a collection of documents.
- This measure comes from information retrieval community
- TF: Term Frequency   IDF: Inverse Document Frequency
- Score = TF x IDF
- Balance the number of times a term appears in a document (TF) against the number of documents in which the term appears (IDF).
- TF-IDF can differ for the same word in two different documents (because the TF could be different)
- Select the overall highest TF*IDF scores for any text document.

TF-IDF Example

Text 1	i love natural language processing but i hate python
Text 2	i like image processing
Text 3	i like signal processing and image processing

Term Frequency (TF)

	and	but	hate	i	image	language	like	love	natural	processing	python	signal
Text 1	0	1	1	2	0	1	0	1	1	1	1	0
Text 2	0	0	0	1	1	0	1	0	0	1	0	0
Text 3	1	0	0	1	1	0	1	0	0	2	0	1

Inverse Document Frequence (IDF)

Term	and	but	hate	i	image	language	like	love	natural	processing	python	signal
IDF	0.47712	0.47712	0.4771	0	0.1760913	0.477121	0.1760913	0.477121	0.47712125	0	0.477121	0.477121

TF*IDF Example

Text 1	i love natural language processing but i hate python
Text 2	i like image processing
Text 3	i like signal processing and image processing

TF x IDF

	and	but	hate	i	image	language	like	love	natural	processing	python	signal
Text 1	0	0.47712	0.4771	0	0	0.477121	0	0.477121	0.47712125	0	0.477121	0
Text 2	0	0	0	0	0.1760913	0	0.1760913	0	0	0	0	0
Text 3	0.47712	0	0	0	0.1760913	0	0.1760913	0	0	0	0	0.477121

TF*IDF Limitations

- It is only useful as a lexical level feature.
- It does not capture sematic meaning.
- The highest TF-IDF score may not make sense with the topic of the document, since IDF gives high weigh if the DF of a term is low.
- It neglects the sequence of the terms.

Scikit-learn

scikit-learn

- from sklearn.feature_extraction.text import CountVectorizer
- from sklearn.linear_model import TfidfTransformer
- from sklearn.linear_model import TfidfVectorizer

Count Vectorizer Documentation

https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html

TFIDF Transformer Documentation

https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfTransformer.html

TFIDF Vectorizer Documentation (2 steps all at once)

https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html

Part 3:
Model Training

Load Data: Pandas DataFrame

```
df_wine.shape
```

Number of instances

```
(1599, 12)
```

Number of attributes

```
df_wine.head(5)
```

Columns/Attributes

Rows/Instances

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

Source: Amazon Web Services

ML Algorithms

- Let’s watch this video that introduces the following main ML algorithms:
  - Linear Regression
  - Naïve Bayes
  - Decision Tree
  - Logistic Regression
  - Neural Networks
  - Support Vector Machine

- A Friendly Introduction to Machine Learning (taught by Luis Serrano on YouTube, 00:00-20:04))

  https://www.youtube.com/watch?v=IpGxLWOIZy4

Model Fitting

scikit-learn

- from sklearn.tree import DecisionTreeClassifier
- from sklearn.linear_model import LinearRegression
- from sklearn.naive_bayes import MultinomialNB
- from sklearn.linear_model import LogisticRegression
- from sklearn.svm import SVC

Linear Regression Documentation

https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html

Linear Regression Example

https://scikit-learn.org/stable/auto_examples/linear_model/plot_ols.html

Model Prediction

scikit-learn

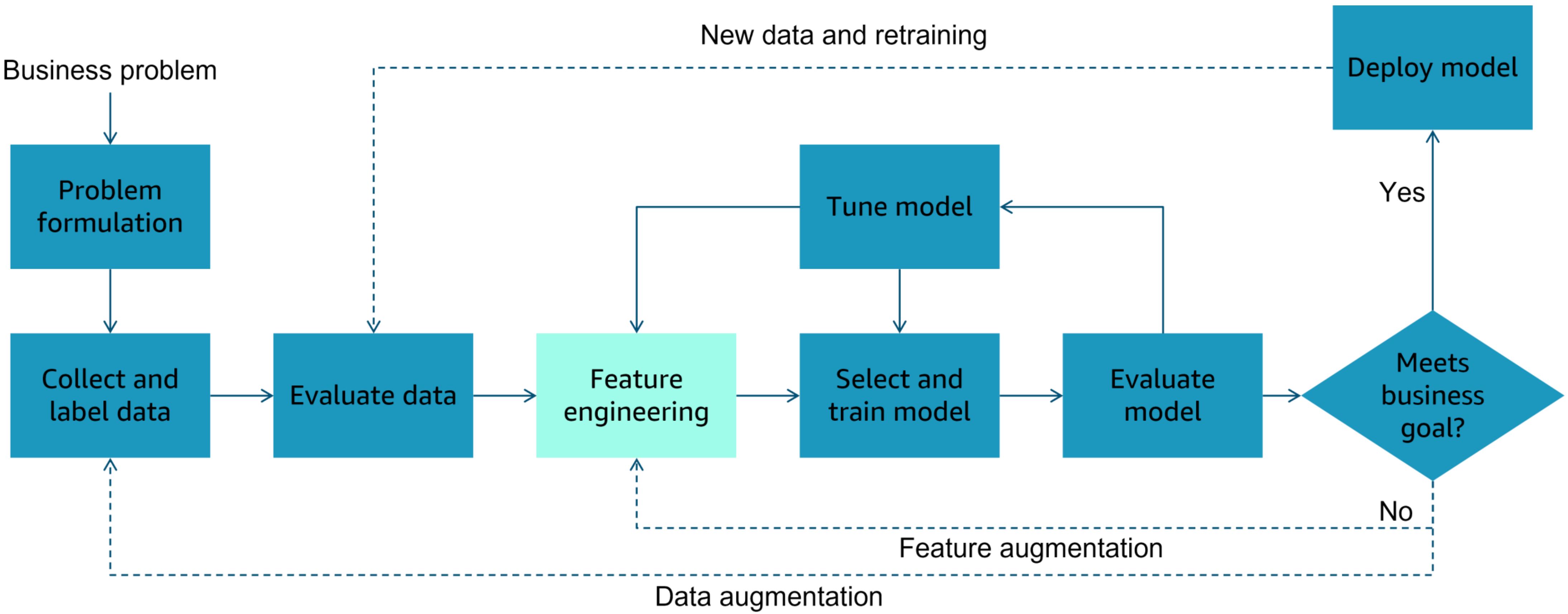
- model.predict(X_test)
- model.predict_proba(X_test)

Logistic Regression Documentation & Example

https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

Part 4
Performance Evaluation

ML Workflow: Evaluate Model



Evaluating Model Performance

- After training, you need to evaluate your model performance.
- How good is a model? (How well is my model doing?)
- Which model is better?
- How do I improve it?
- How do I determine which model works well?

Metrics For Performance Evaluation

- Focus on the predictive capability of a model
- Rather than how fast it takes to classify or build models, etc.
- For classification tasks:
  - Accuracy
  - Precision
  - Recall
  - F1

Metrics For Performance Evaluation – Cont’

- **Evaluation Metrics:**
  - Accuracy
  - Precision
  - Recall
  - F1

- **Confusion Matrix** for a binary classification (2 label class)

	Predicted Class		
Actual Class		Class = Yes	Class = No
	Class = Yes	A	B
	Class = No	C	D

A: TP (True Positive)

B: FN (False Negative)

C: FP (False Positive)

D: TN (True Negative)

Evaluation Metrics

- Let's watch this video that explains about evaluation metrics used for assessing model performance.
- Machine Learning: Testing and Error Metrics
(taught by Luis Serrano on YouTube, 05:39-24:56)

  https://www.youtube.com/watch?v=aDW44NPhNw0

Evaluation Measures – Cont’

- **Confusion Matrix** for a binary classification (2 label class)

	Predicted Class	
Actual Class	Class = Yes	Class = No
Class = Yes	A: TP	B (FN)
Class = No	C: FP	D (TN)

A: TP (True Positive)

B: FN (False Negative)

C: FP (False Positive)

D: TN (True Negative)

- Accuracy is the percentage of correct Yes and No out of all example.

  Accuracy = (A+D)/ (A+B+C+D) = (TP+TN) / (TP+TN+FP+FN)

Evaluation Measures – Cont'

	Predicted Class	
Actual Class	Class = Yes	Class = No
Class = Yes	A: TP	B (FN)
Class = No	C: FP	D (TN)

A: TP (True Positive)
B: FN (False Negative)
C: FP (False Positive)
D: TN (True Negative)

- Precision is the percentage of predicted Yes answers that are right
  Precision = TP / (TP + FP)
- Recall is the percentage of actual Yes answers that are right
  Precision = TP / (TP + FN)
- F1 is the harmonic mean of recall and precision
  F1 = 2 * (Recall * Precision) / (Recall + Precision)

Evaluation Metrics: Scikit-learn

- sklearn.metrics.confusion_matrix()

https://scikit-learn.org/stable/modules/generated/sklearn.metrics.confusion_matrix.html

```
>>> from sklearn.metrics import confusion_matrix
>>> y_true = [2, 0, 2, 2, 0, 1]
>>> y_pred = [0, 0, 2, 2, 0, 2]
>>> confusion_matrix(y_true, y_pred)
array([[2, 0, 0],
       [0, 0, 1],
       [1, 0, 2]])
```

- sklearn.metrics. classification_report()

https://scikit-learn.org/stable/modules/generated/sklearn.metrics.classification_report.html

```
>>> from sklearn.metrics import classification_report
>>> y_true = [0, 1, 2, 2, 2]
>>> y_pred = [0, 0, 2, 2, 1]
>>> target_names = ['class 0', 'class 1', 'class 2']
>>> print(classification_report(y_true, y_pred, target_names=target_names))
              precision    recall  f1-score   support

     class 0       0.50      1.00      0.67         1
     class 1       0.00      0.00      0.00         1
     class 2       1.00      0.67      0.80         3

    accuracy                           0.60         5
   macro avg       0.50      0.56      0.49         5
weighted avg       0.70      0.60      0.61         5
```

Evaluation Metrics: Scikit-learn – Cont’

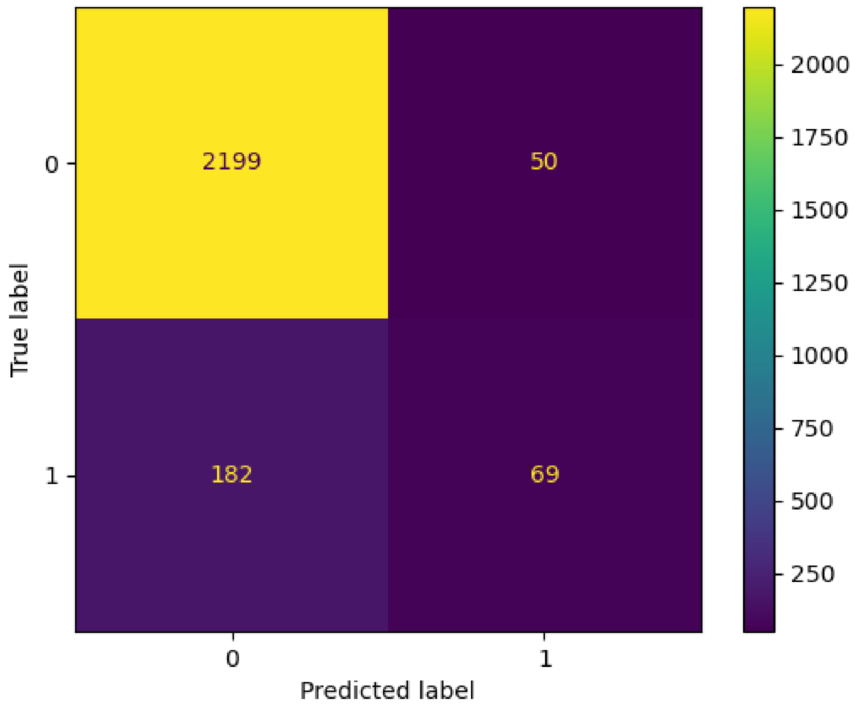
- sklearn.metrics.ConfusionMatrixDisplay()

https://scikit-learn.org/stable/auto_examples/release_highlights/plot_release_highlights_1_5_0.html#sphx-glr-auto-examples-release-highlights-plot-release-highlights-1-5-0-py

```
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import ConfusionMatrixDisplay


X, y = make_classification(n_samples=10_000, weights=[0.9, 0.1], random_state=0)
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)

classifier_05 = LogisticRegression(C=1e6, random_state=0).fit(X_train, y_train)
_ = ConfusionMatrixDisplay.from_estimator(classifier_05, X_test, y_test)
```



Questions or Comments?

Thank You!