Classification

ACTL3143 & ACTL5111 Deep Learning for Actuaries

Patrick Laub

UNSW SYDNEY

Lecture Outline

- **Classification**
- Stroke Prediction

Iris dataset

```python
from sklearn.datasets import load_iris
iris = load_iris()
names = ["SepalLength", "SepalWidth", "PetalLength", "PetalWidth"]
features = pd.DataFrame(iris.data, columns=names)
features
```

	SepalLength	SepalWidth	PetalLength	PetalWidth
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
…	…	…	…	…
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

150 rows × 4 columns

Target variable

```python
iris.target_names
```

```
array(['setosa', 'versicolor', 'virginica'],
dtype='<U10')
```

```python
iris.target[:8]
```

```
array([0, 0, 0, 0, 0, 0, 0, 0])
```

```python
target = iris.target
target = target.reshape(-1, 1)
target[:8]
```

```
array([[0],
       [0],
       [0],
       [0],
       [0],
       [0],
       [0],
       [0]])
```

```python
classes, counts = np.unique(
        target,
        return_counts=True
)
print(classes)
print(counts)
```

```
[0 1 2]
[50 50 50]
```

```python
iris.target_names[
  target[[0, 30, 60]]
]
```

```
array([['setosa'],
       ['setosa'],
       ['versicolor']], dtype='<U10')
```

Split the data into train and test

```python
X_train, X_test, y_train, y_test = train_test_split(features, target, random_state=24)
X_train
```

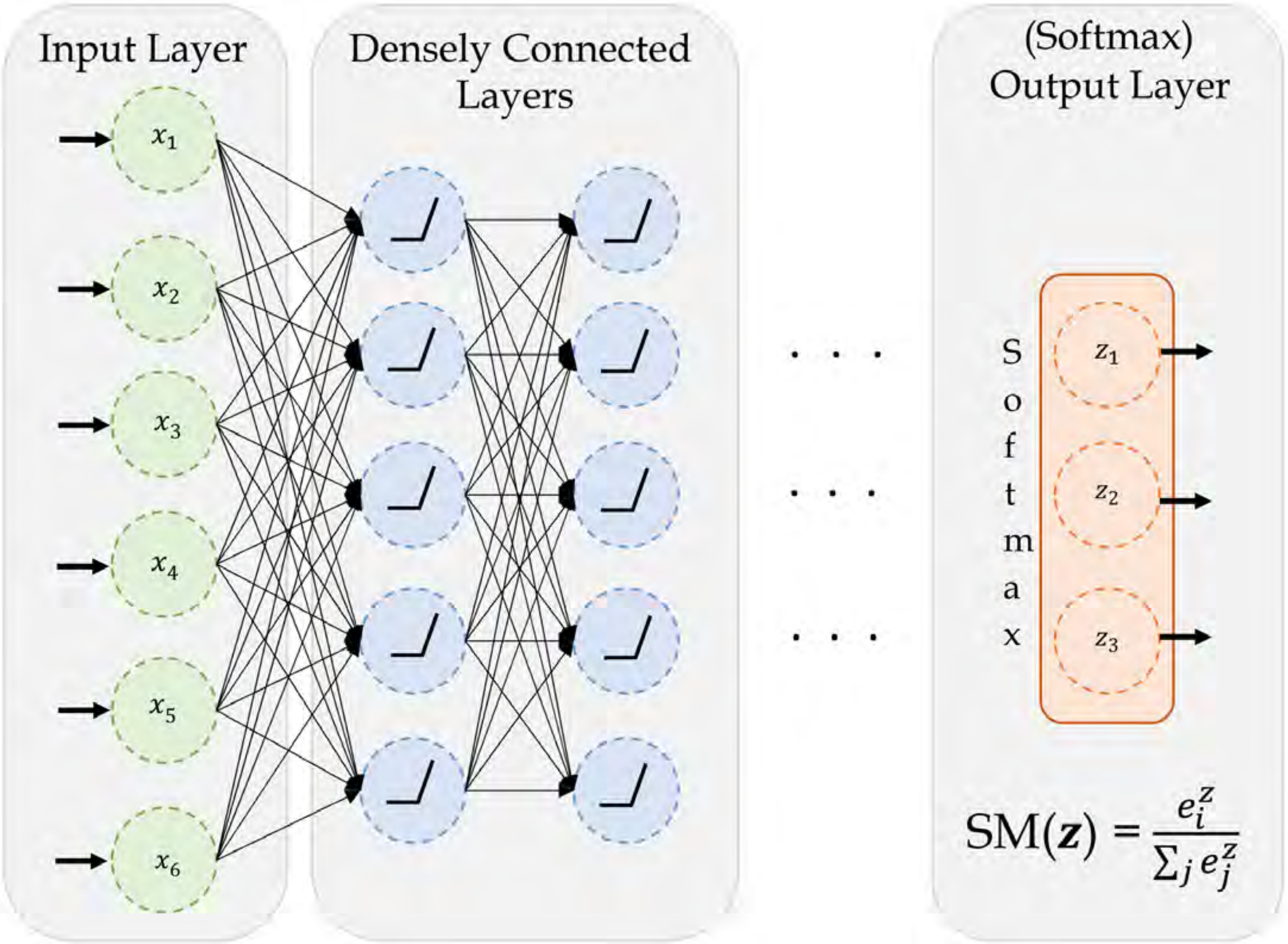
	SepalLength	SepalWidth	PetalLength	PetalWidth
53	5.5	2.3	4.0	1.3
58	6.6	2.9	4.6	1.3
95	5.7	3.0	4.2	1.2
…	…	…	…	…
145	6.7	3.0	5.2	2.3
87	6.3	2.3	4.4	1.3
131	7.9	3.8	6.4	2.0

112 rows × 4 columns

```python
X_test.shape, y_test.shape
```

```
((38, 4), (38, 1))
```

A basic classifier network



A basic network for classifying into three categories.

Source: Marcus Lautier (2022).

Create a classifier model

```
NUM_FEATURES = len(features.columns)
NUM_CATS = len(np.unique(target))

print("Number of features:", NUM_FEATURES)
print("Number of categories:", NUM_CATS)
```

```
Number of features: 4
Number of categories: 3
```

Make a function to return a Keras model:

```
def build_model(seed=42):
    random.seed(seed)
    return Sequential([
        Dense(30, activation="relu"),
        Dense(NUM_CATS, activation="softmax")
    ])
```

Fit the model

```
model = build_model()
model.compile("adam", "sparse_categorical_crossentropy")

model.fit(X_train, y_train, epochs=5, verbose=2);
```

```
Epoch 1/5
4/4 - 1s - 172ms/step - loss: 1.3502
Epoch 2/5
4/4 - 0s - 5ms/step - loss: 1.2852
Epoch 3/5
4/4 - 0s - 6ms/step - loss: 1.2337
Epoch 4/5
4/4 - 0s - 15ms/step - loss: 1.1915
Epoch 5/5
4/4 - 0s - 15ms/step - loss: 1.1556
```

Track accuracy as the model trains

```python
model = build_model()
model.compile("adam", "sparse_categorical_crossentropy", metrics=["accuracy"])
model.fit(X_train, y_train, epochs=5, verbose=2);
```

```
Epoch 1/5
4/4 - 1s - 154ms/step - accuracy: 0.2946 - loss: 1.3502
Epoch 2/5
4/4 - 0s - 6ms/step - accuracy: 0.3036 - loss: 1.2852
Epoch 3/5
4/4 - 0s - 6ms/step - accuracy: 0.3036 - loss: 1.2337
Epoch 4/5
4/4 - 0s - 5ms/step - accuracy: 0.3304 - loss: 1.1915
Epoch 5/5
4/4 - 0s - 6ms/step - accuracy: 0.3393 - loss: 1.1556
```

Run a long fit

```
model = build_model()
model.compile("adam", "sparse_categorical_crossentropy", \
        metrics=["accuracy"])
%time hist = model.fit(X_train, y_train, epochs=500, \
        validation_split=0.25, verbose=False)
```

```
CPU times: user 19.9 s, sys: 2.24 s, total: 22.1 s
Wall time: 20.7 s
```

Evaluation now returns both *loss* and *accuracy*.

```
model.evaluate(X_test, y_test, verbose=False)
```

```
[0.09586220979690552, 0.9736841917037964]
```

Add early stopping

```python
model = build_model()
model.compile("adam", "sparse_categorical_crossentropy", \
        metrics=["accuracy"])

es = EarlyStopping(restore_best_weights=True, patience=50,
        monitor="val_accuracy")
%time hist_es = model.fit(X_train, y_train, epochs=500, \
        validation_split=0.25, callbacks=[es], verbose=False);

print(f"Stopped after {len(hist_es.history['loss'])} epochs.")
```

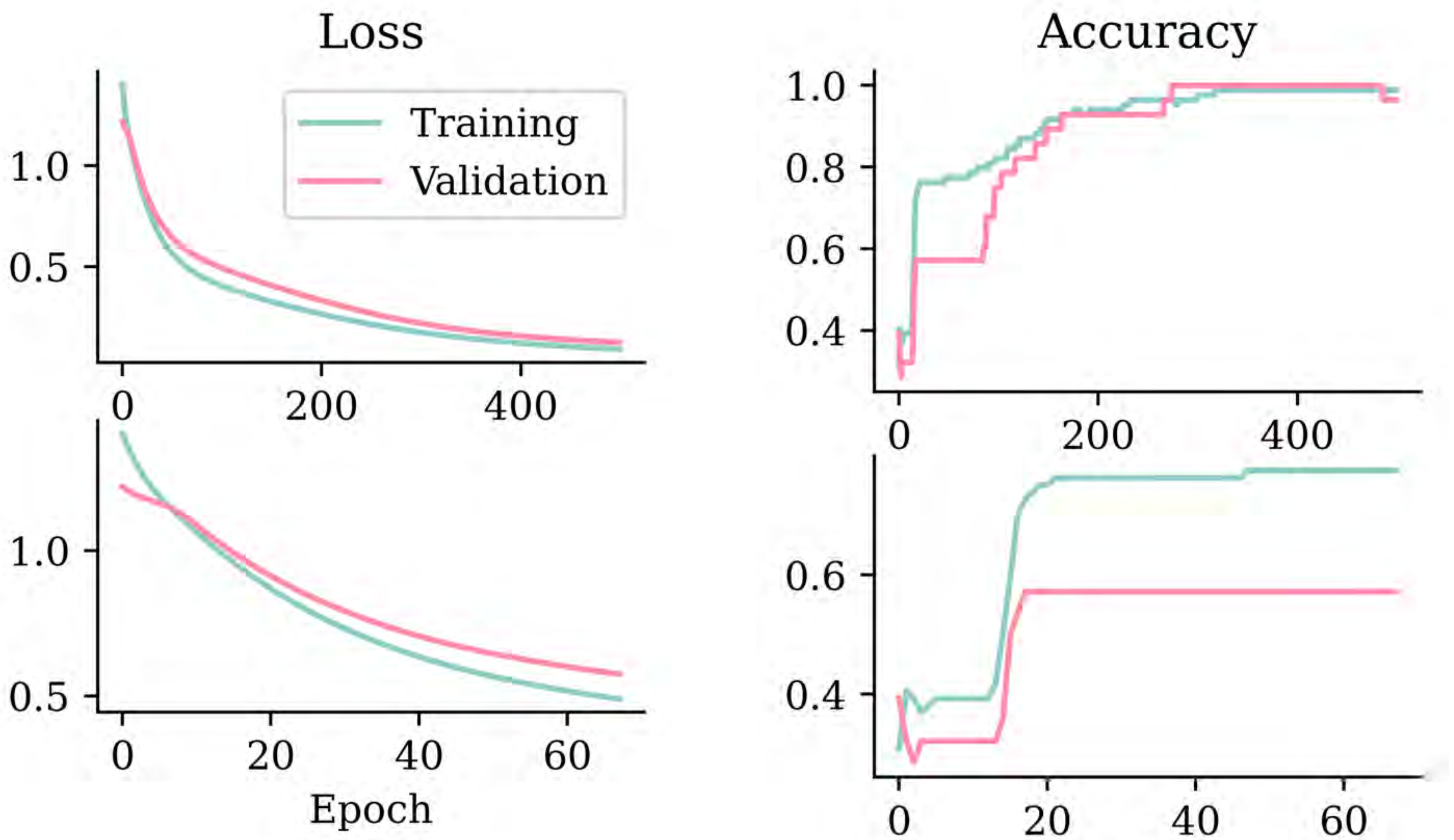
```
CPU times: user 4.15 s, sys: 388 ms, total: 4.53 s
Wall time: 4.06 s
Stopped after 68 epochs.
```

Evaluation on test set:

```python
model.evaluate(X_test, y_test, verbose=False)
```

```
[0.9856260418891907, 0.5263158082962036]
```

Fitting metrics



What is the softmax activation?

It creates a “probability” vector: $\text{Softmax}(\boldsymbol{x}) = \frac{e^{x}_i}{\sum_j e^{x}_j}$.

In NumPy:

```python
out = np.array([5, -1, 6])
(np.exp(out) / np.exp(out).sum()).round(3)
```

```
array([0.269, 0.001, 0.731])
```

In Keras:

```python
out = keras.ops.convert_to_tensor([[5.0, -1.0, 6.0]])
keras.ops.round(keras.ops.softmax(out), 3)
```

```
<tf.Tensor: shape=(1, 3), dtype=float32, numpy=array([[0.269, 0.001, 0.731]], dtype=float32)>
```

Prediction using classifiers

```python
y_test[:4]
```

```
array([[2],
       [2],
       [1],
       [1]])
```

```python
y_pred = model.predict(X_test.head(4), verbose=0)
y_pred
```

```
array([[0.1397096 , 0.5175301 , 0.34276026],
       [0.24611065, 0.44371164, 0.3101777 ],
       [0.26309973, 0.43174297, 0.3051573 ],
       [0.259089  , 0.44883674, 0.29207426]], dtype=float32)
```

```python
# Add 'keepdims=True' to get a column vector.
np.argmax(y_pred, axis=1)
```

```
array([1, 1, 1, 1])
```

```python
iris.target_names[np.argmax(y_pred, axis=1)]
```

```
array(['versicolor', 'versicolor', 'versicolor', 'versicolor'],
      dtype='<U10')
```

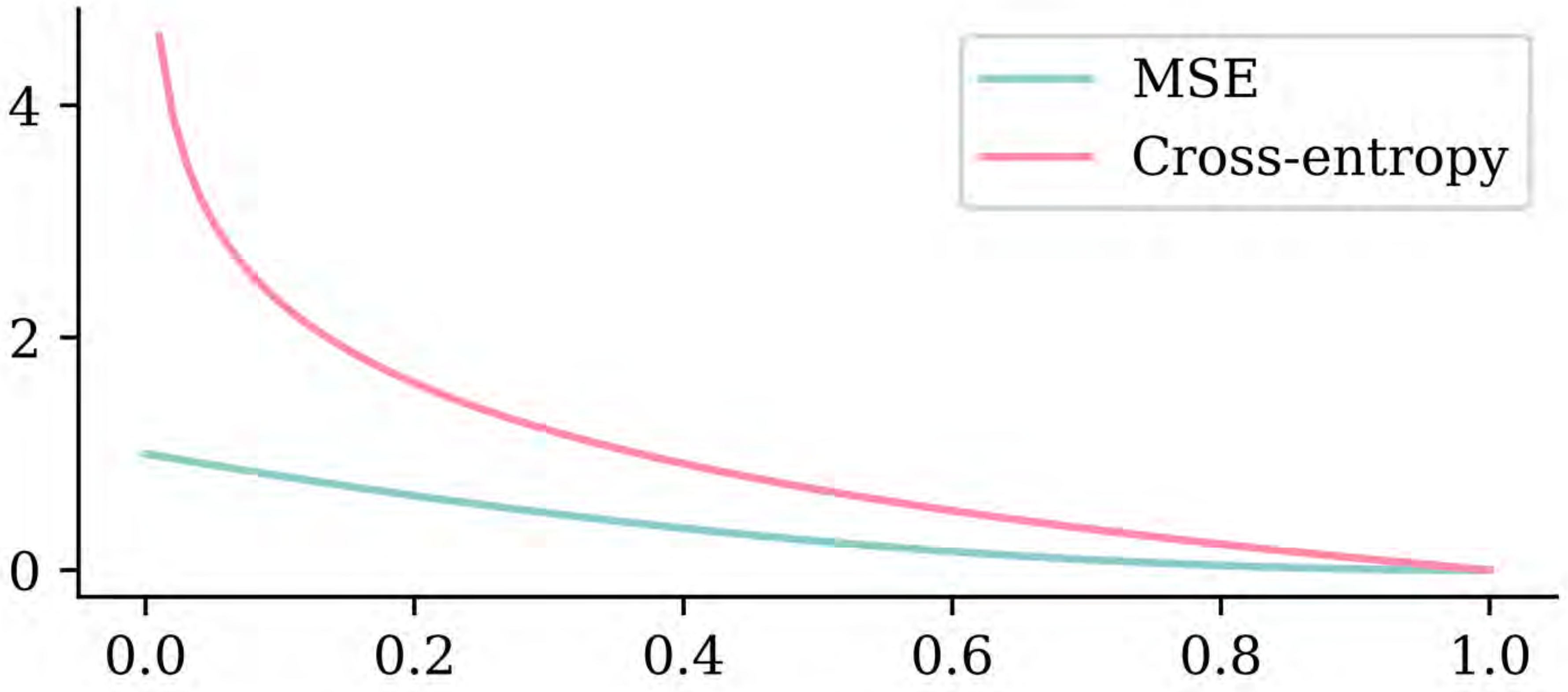
Cross-entropy loss: ELI5

Neural Networks Part 6: Cross Entropy

Neural Networks Part 7: Cross Entropy Derivativ…

Why use cross-entropy loss?

```
p = np.linspace(0, 1, 100)
plt.plot(p, (1 - p) ** 2)
plt.plot(p, -np.log(p))
plt.legend(["MSE", "Cross-entropy"]);
```



One-hot encoding

```python
from sklearn.preprocessing import OneHotEncoder

enc = OneHotEncoder(sparse_output=False)

y_train_oh = enc.fit_transform(y_train)
y_test_oh = enc.transform(y_test)
```

```python
y_train[:5]
```

```
array([[1],
       [1],
       [1],
       [0],
       [0]])
```

```python
y_train_oh[:5]
```

	x0_0	x0_1	x0_2
0	0.0	1.0	0.0
1	0.0	1.0	0.0
2	0.0	1.0	0.0
3	1.0	0.0	0.0
4	1.0	0.0	0.0

Classifier given one-hot outputs

Create the model (*new loss function*):

```
model = build_model()
model.compile("adam", "categorical_crossentropy", \
    metrics=["accuracy"])
```

Fit the model (*new target variables*):

```
model.fit(X_train, y_train_oh, epochs=100, verbose=False);
```

Evaluate the model (*new target variables*):

```
model.evaluate(X_test, y_test_oh, verbose=False)
```

```
[0.347093790769577, 0.9473684430122375]
```

Lecture Outline

- Classification
- **Stroke Prediction**

The data

Dataset source: Kaggle Stroke Prediction Dataset.

```
data = pd.read_csv("stroke.csv")
data.head()
```

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residenc
0	9046	Male	67.0	0	1	Yes	Private	Urban
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural
2	31112	Male	80.0	0	1	Yes	Private	Rural
3	60182	Female	49.0	0	0	Yes	Private	Urban
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural

Data description

1. `id`: unique identifier
2. `gender`: “Male”, “Female” or “Other”
3. `age`: age of the patient
4. `hypertension`: 0 or 1 if the patient has hypertension
5. `heart_disease`: 0 or 1 if the patient has any heart disease
6. `ever_married`: “No” or “Yes”
7. `work_type`: “children”, “Govt_jov”, “Never_worked”, “Private” or “Self-employed”
8. `Residence_type`: “Rural” or “Urban”
9. `avg_glucose_level`: average glucose level in blood
10. `bmi`: body mass index
11. `smoking_status`: “formerly smoked”, “never smoked”, “smokes” or “Unknown”
12. `stroke`: 0 or 1 if the patient had a stroke

Source: Kaggle, Stroke Prediction Dataset.

Split the data

First, look for missing values.

```
number_missing = data.isna().sum()
number_missing[number_missing > 0]
```

```
bmi    201
dtype: int64
```

```
features = data.drop(["id", "stroke"], axis=1)
target = data["stroke"]

X_main, X_test, y_main, y_test = train_test_split(
    features, target, test_size=0.2, random_state=7)
X_train, X_val, y_train, y_val = train_test_split(
    X_main, y_main, test_size=0.25, random_state=12)

X_train.shape, X_val.shape, X_test.shape
```

```
((3066, 10), (1022, 10), (1022, 10))
```

What values do we see in the data?

```
X_train["gender"].value_counts()
```

```
gender
Female     1802
Male       1264
Name: count, dtype: int64
```

```
X_train["ever_married"].value_counts()
```

```
ever_married
Yes    2007
No     1059
Name: count, dtype: int64
```

```
X_train["Residence_type"].value_counts(
```

```
Residence_type
Urban    1536
Rural    1530
Name: count, dtype: int64
```

```
X_train["work_type"].value_counts()
```

```
work_type
Private          1754
Self-employed     490
children          419
Govt_job          390
Never_worked       13
Name: count, dtype: int64
```

```
X_train["smoking_status"].value_counts(
```

```
smoking_status
never smoked       1130
Unknown             944
formerly smoked     522
smokes              470
Name: count, dtype: int64
```

Preprocess columns individually

1. Take categorical columns $\hookrightarrow$ one-hot vectors
2. binary columns $\hookrightarrow$ do nothing
3. continuous columns $\hookrightarrow$ impute NaNs & standardise.

Scikit-learn column transformer

```python
from sklearn.pipeline import make_pipeline

cat_vars =  ["gender", "ever_married", "Residence_type",
    "work_type", "smoking_status"]

ct = make_column_transformer(
  (OneHotEncoder(sparse_output=False, handle_unknown="ignore"), cat_vars),
  ("passthrough", ["hypertension", "heart_disease"]),
  remainder=make_pipeline(SimpleImputer(), StandardScaler()),
  verbose_feature_names_out=False
)

X_train_ct = ct.fit_transform(X_train)
X_val_ct = ct.transform(X_val)
X_test_ct = ct.transform(X_test)

for name, X in zip(("train", "val", "test"), (X_train_ct, X_val_ct, X_test_ct)):
    num_na = X.isna().sum().sum()
    print(f"The {name} set has shape {X.shape} & with {num_na} NAs.")
```

```
The train set has shape (3066, 20) & with 0 NAs.
The val set has shape (1022, 20) & with 0 NAs.
The test set has shape (1022, 20) & with 0 NAs.
```

Handling unseen categories

```
1 X_train["gender"].value_counts()
```

```
gender
Female     1802
Male       1264
Name: count, dtype: int64
```

```
1 X_val["gender"].value_counts()
```

```
gender
Female    615
Male      406
Other       1
Name: count, dtype: int64
```

```
ind = np.argmax(X_val["gender"] == "Oth
X_val.iloc[ind-1:ind+3][["gender"]]
```

	gender
4970	Male
3116	Other
4140	Male
2505	Female

```
gender_cols = X_val_ct[["gender_Female"
gender_cols.iloc[ind-1:ind+3]
```

	gender_Female	gender_
4970	0.0	1.0
3116	0.0	0.0
4140	0.0	1.0
2505	1.0	0.0

Setup a binary classification model

```
def create_model(seed=42):
    random.seed(seed)
    model = Sequential()
    model.add(Input(X_train_ct.shape[1:]))
    model.add(Dense(32, "leaky_relu"))
    model.add(Dense(16, "leaky_relu"))
    model.add(Dense(1, "sigmoid"))
    return model
```

```
model = create_model()
model.summary()
```

```
Model: "sequential_5"
```

Layer (type)	Output Shape	Param #
dense_10 (Dense)	(None, 32)	672
dense_11 (Dense)	(None, 16)	528
dense_12 (Dense)	(None, 1)	17

```
Total params: 1,217 (4.75 KB)
Trainable params: 1,217 (4.75 KB)
Non-trainable params: 0 (0.00 B)
```

Add metrics, compile, and fit

```python
model = create_model()

pr_auc = keras.metrics.AUC(curve="PR", name="pr_auc")
model.compile(optimizer="adam", loss="binary_crossentropy",
    metrics=[pr_auc, "accuracy", "auc"])

es = EarlyStopping(patience=50, restore_best_weights=True,
    monitor="val_pr_auc", verbose=1)
model.fit(X_train_ct, y_train, callbacks=[es], epochs=1_000, verbose=0,
  validation_data=(X_val_ct, y_val));
```

```
Epoch 65: early stopping
Restoring model weights from the end of the best epoch: 15.
```

```python
model.evaluate(X_val_ct, y_val, verbose
```

```
[0.14444081485271454,
 0.13122102618217468,
 0.9589040875434875,
 0.8215014934539795]
```

Overweight the minority class

```python
model = create_model()

pr_auc = keras.metrics.AUC(curve="PR", name="pr_auc")
model.compile(optimizer="adam", loss="binary_crossentropy",
    metrics=[pr_auc, "accuracy", "auc"])

es = EarlyStopping(patience=50, restore_best_weights=True,
    monitor="val_pr_auc", verbose=1)
model.fit(X_train_ct, y_train.to_numpy(), callbacks=[es], epochs=1_000, verbose=0,
  validation_data=(X_val_ct, y_val), class_weight={0: 1, 1: 10});
```

```
Epoch 74: early stopping
Restoring model weights from the end of the best epoch: 24.
```

```python
model.evaluate(X_val_ct, y_val, verbose
```

```
[0.3345569670200348,
 0.13615098595619202,
 0.8062622547149658,
 0.8122206330299377]
```

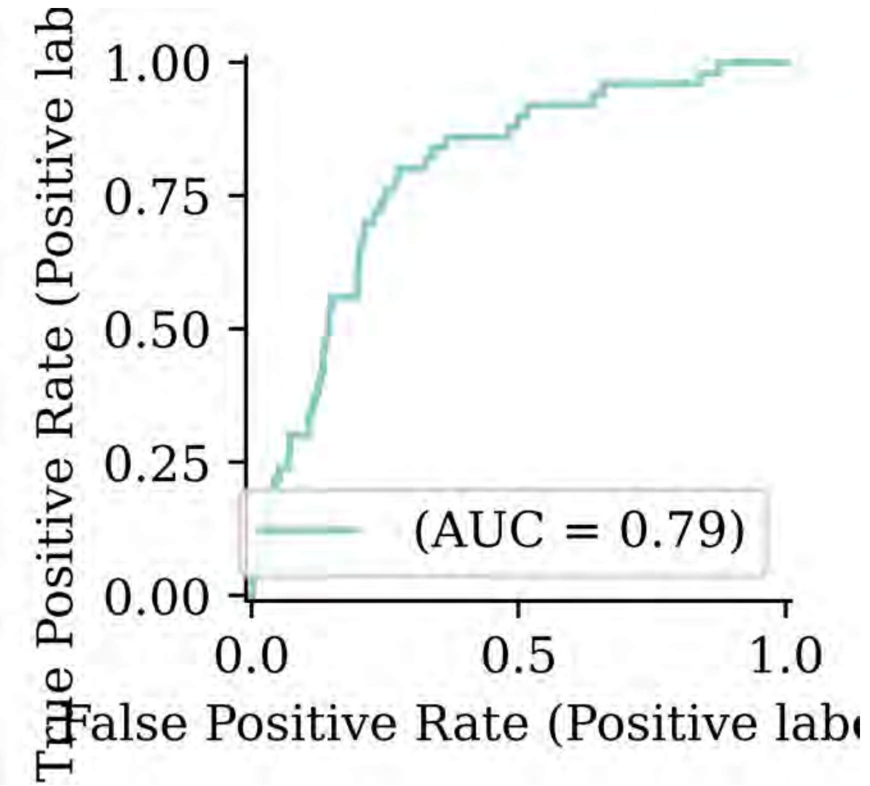
```python
model.evaluate(X_test_ct, y_test, verbo
```

```
[0.3590189516544342,
 0.1449822038412094,
 0.8023483157157898,
 0.7915638089179993]
```

Classification Metrics

```
from sklearn.metrics import confusion_matrix, RocCurveDisplay, PrecisionRecallDisplay
y_pred = model.predict(X_test_ct, verbose=0)
```

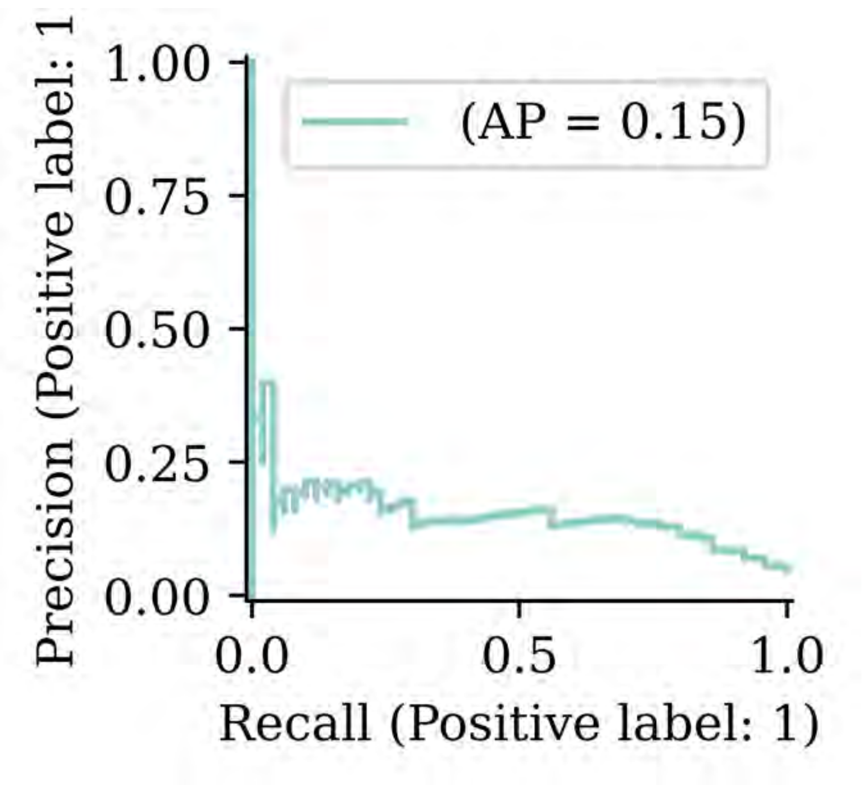
```
RocCurveDisplay.from_predictions(y_test, y_pred, name="");
```




```
y_pred_stroke = y_pred > 0.5
confusion_matrix(y_test, y_pred_stroke)
```

```
array([[792, 180],
       [ 22,  28]])
```

```
PrecisionRecallDisplay.from_predictions(y_test, y_pred, na
```




```
y_pred_stroke = y_pred > 0.3
confusion_matrix(y_test, y_pred_stroke)
```

```
array([[662, 310],
       [ 10,  40]])
```

Package Versions

```python
from watermark import watermark
print(watermark(python=True, packages="keras,matplotlib,numpy,pandas,seaborn,scipy,torch
```

```
Python implementation: CPython
Python version       : 3.11.9
IPython version      : 8.24.0

keras     : 3.3.3
matplotlib: 3.9.0
numpy     : 1.26.4
pandas    : 2.2.2
seaborn   : 0.13.2
scipy     : 1.11.0
torch     : 2.0.1
tensorflow: 2.16.1
tf_keras  : 2.16.0
```

Glossary

- classification problem
- confusion matrix
- cross-entropy loss
- sigmoid activation function