# Classification

ACTL3143 & ACTL5111 Deep Learning for Actuaries

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## Lecture Outline

- **TLDR**
- Classification
- Stroke Prediction

# Classification models in Keras

If the number of classes is $c$, then:

| Target | Output Layer | Loss Function |
|---|---|---|
| Binary ($c = 2$) | 1 neuron with `sigmoid` activation | Binary Cross-Entropy |
| Multi-class ($c > 2$) | $c$ neurons with `softmax` activation | Categorical Cross-Entropy |

# Optionally output logits

If the number of classes is $c$, then:

| Target | Output Layer | Loss Function |
|---|---|---|
| Binary ($c = 2$) | 1 neuron with `linear` activation | Binary Cross-Entropy (`from_logits=True`) |
| Multi-class ($c > 2$) | $c$ neurons with `linear` activation | Categorical Cross-Entropy (`from_logits=True`) |

# Code examples

## Binary

```
model = Sequential([
  # Skipping the earlier layers
  Dense(1, activation="sigmoid")
])
model.compile(loss="binary_crossentropy")
```

## Multi-class

```
model = Sequential([
  # Skipping the earlier layers
  Dense(n_classes, activation="softmax")
])
model.compile(loss="sparse_categorical_crossentropy")
```

## Binary (logits)

```
from keras.losses import BinaryCrossentropy
model = Sequential([
  # Skipping the earlier layers
  Dense(1, activation="linear")
])
loss = BinaryCrossentropy(from_logits=True)
model.compile(loss=loss)
```

## Multi-class (logits)

```
from keras.losses import SparseCategoricalCrossentropy

model = Sequential([
  # Skipping the earlier layers
  Dense(n_classes, activation="linear")
])
loss = SparseCategoricalCrossentropy(from_logits=True)
model.compile(loss=loss)
```

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# 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

```
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

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

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

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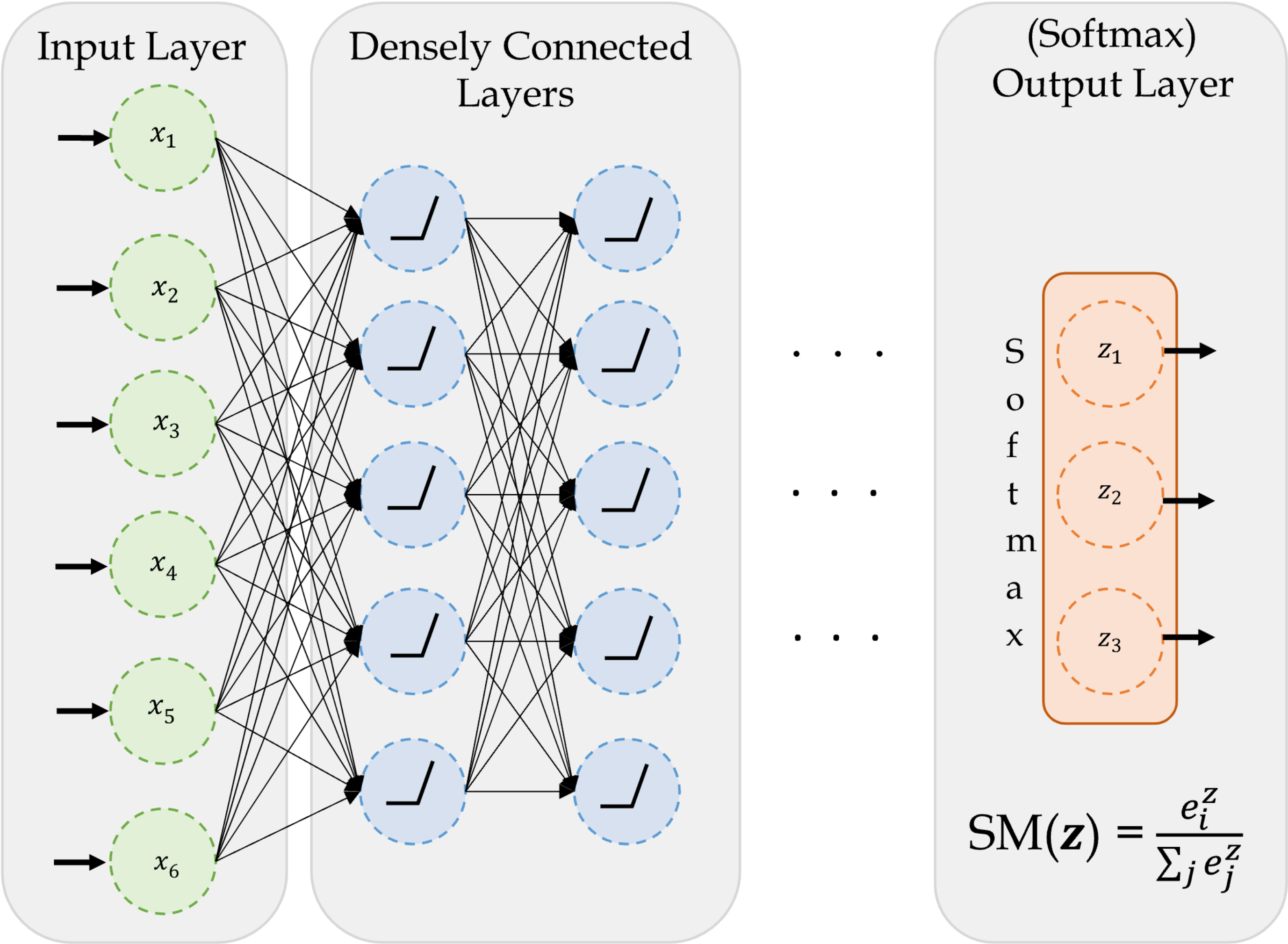
# A basic classifier network




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

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

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

```
Epoch 1/5

4/4 - 0s - 93ms/step - loss: 1.3502
Epoch 2/5
4/4 - 0s - 6ms/step - loss: 1.2852
Epoch 3/5
4/4 - 0s - 6ms/step - loss: 1.2337
Epoch 4/5
4/4 - 0s - 6ms/step - loss: 1.1915
Epoch 5/5
4/4 - 0s - 6ms/step - loss: 1.1556
```

# Track accuracy as the model trains

```
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 - 0s - 91ms/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 - 6ms/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

```python
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 24.5 s, sys: 3.69 s, total: 28.2 s
Wall time: 23.7 s
```

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

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

```
[0.09586219489574432, 0.9736841917037964]
```

# Add early stopping

```
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 3.75 s, sys: 530 ms, total: 4.28 s
Wall time: 3.61 s
Stopped after 68 epochs.
```

## Evaluation on test set:

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

```
[0.9856260418891907, 0.5263158082962036]
```

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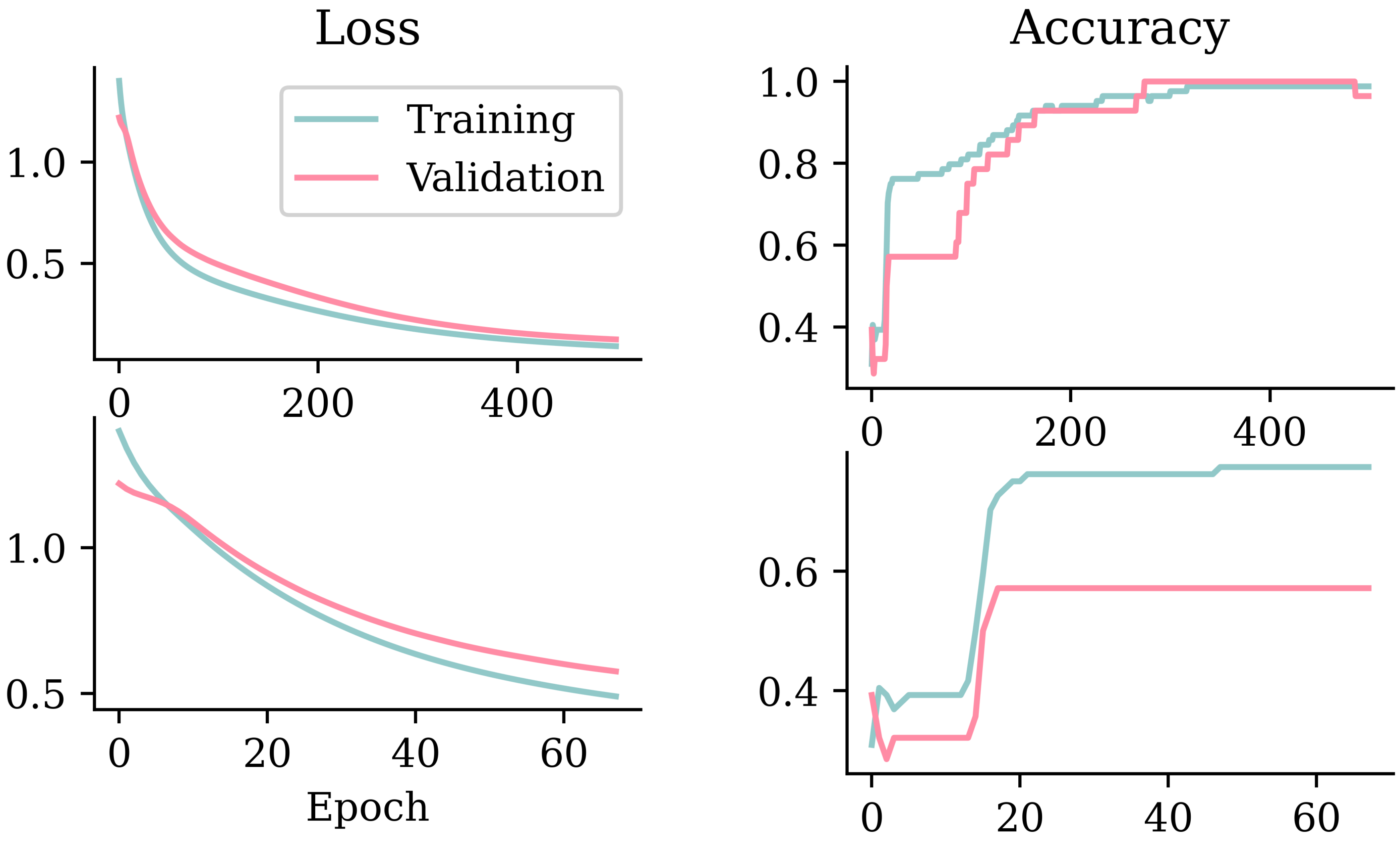
# Fitting metrics



# What is the softmax activation?

It creates a "probability" vector: $\text{Softmax}(\boldsymbol{x}) = \frac{\mathrm{e}^{x}_{i}}{\sum_j \mathrm{e}^{x}_{j}}$.

## In NumPy:

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

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

## In Keras:

```
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

```
y_test[:4]
```

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

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

```
array([[0.1397096 , 0.5175301 , 0.34276026],
       [0.24611066, 0.44371167, 0.31017768],
       [0.26309973, 0.43174297, 0.30515727],
       [0.259089  , 0.44883674, 0.29207426]], dtype=float32)
```

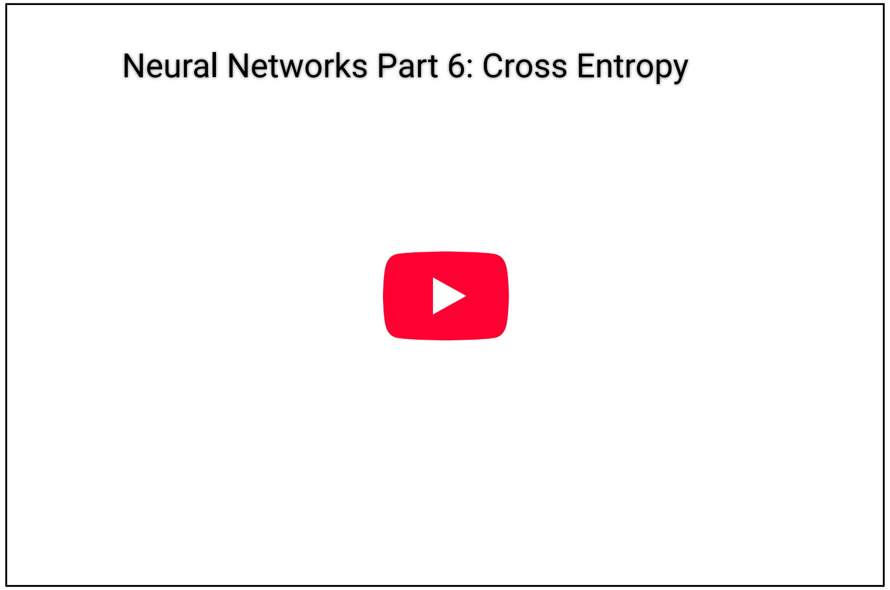
```
# Add 'keepdims=True' to get a column vector.
np.argmax(y_pred, axis=1)
```

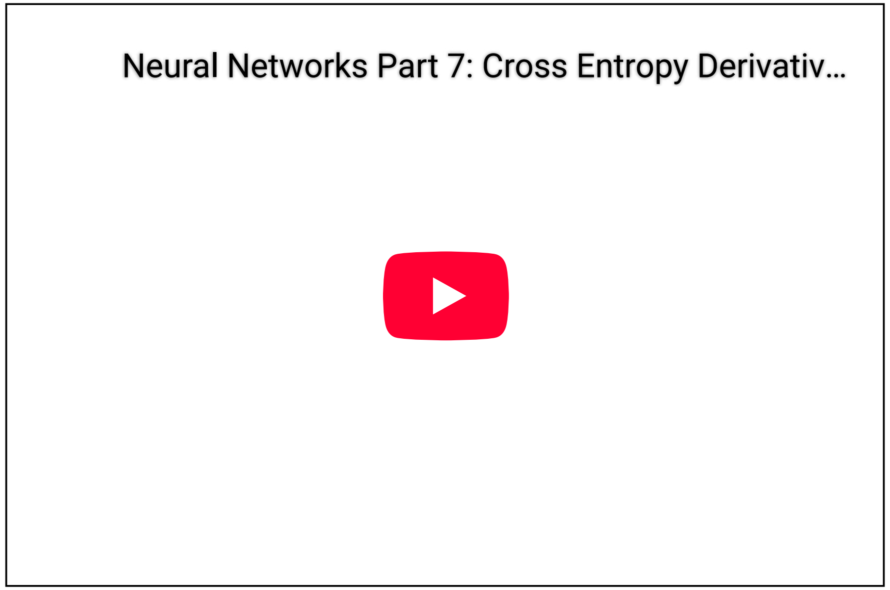
```
array([1, 1, 1, 1])
```

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

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

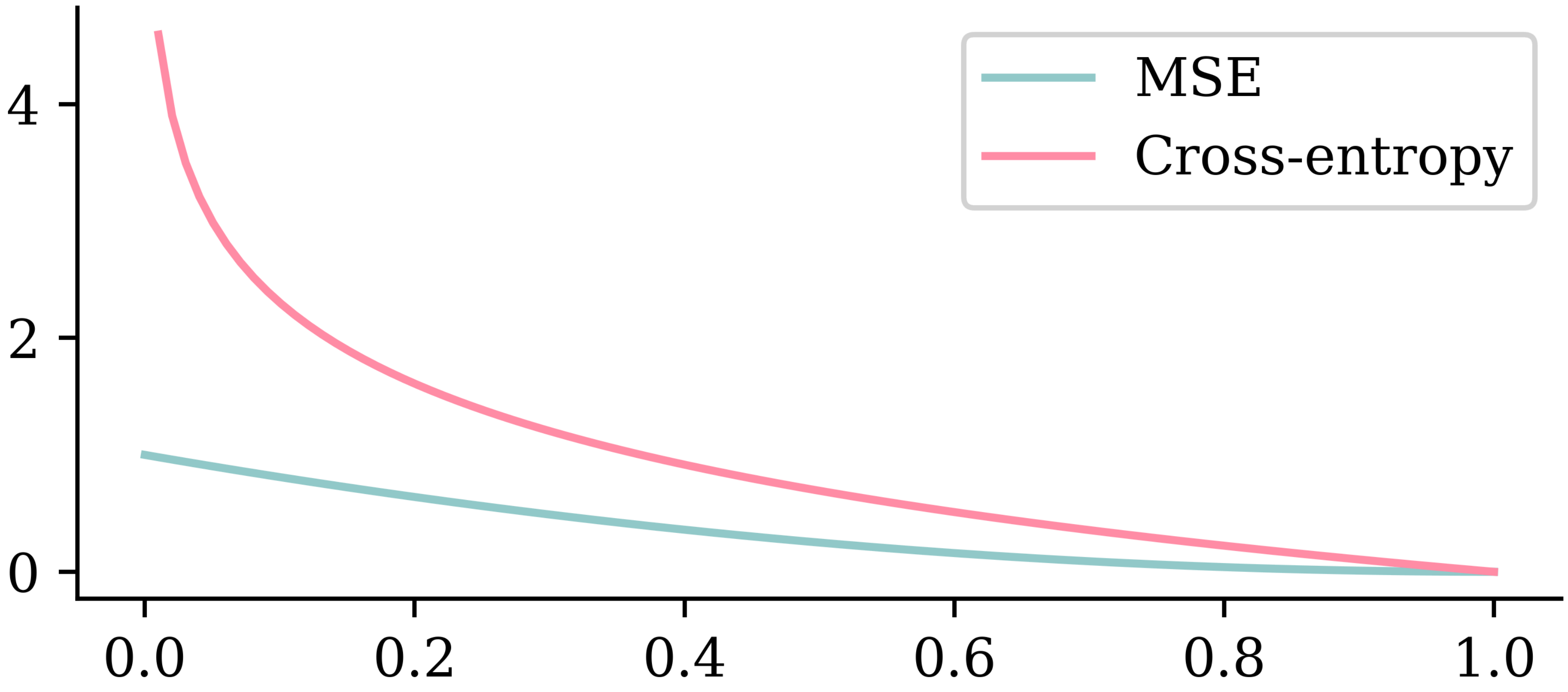
# Cross-entropy loss: ELI5



# Why use cross-entropy loss?

```python
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)
```

```
[0.3470938205718994, 0.9473684430122375]
```

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- **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?

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

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

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

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

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

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

```python
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
```

```python
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

```
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

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

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

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

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

```
ind = np.argmax(X_val["gender"] == "Othe
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

```python
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
```

```python
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

```
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.
```

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

```
[0.14444079995155334,
 0.13122102618217468,
 0.9589040875434875,
 0.8215014934539795]
```

# Overweight the minority class

```
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.
```

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

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

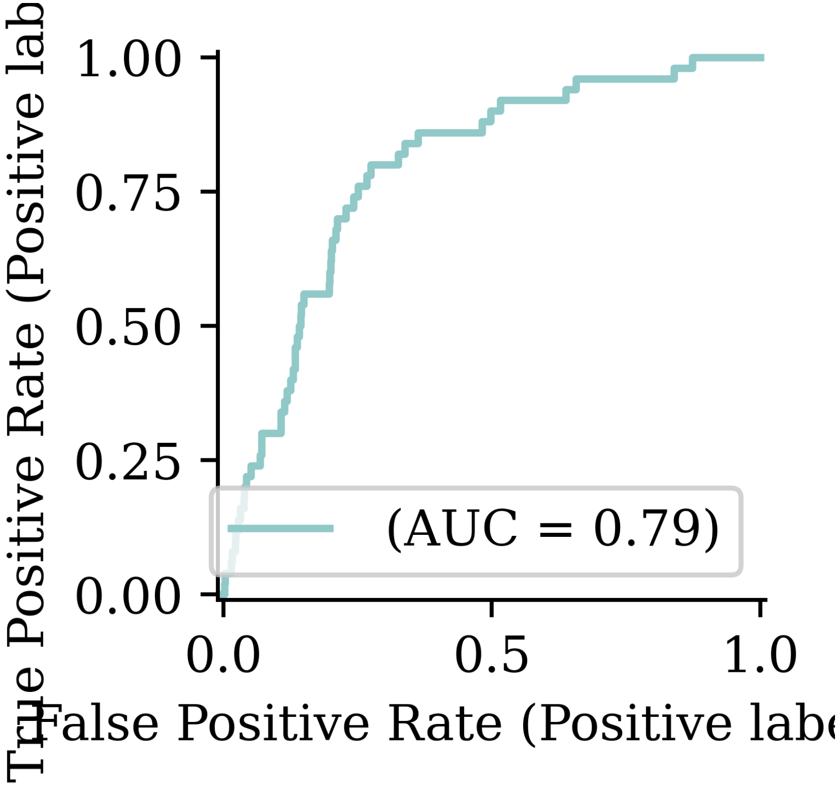
```
model.evaluate(X_test_ct, y_test, verbos
```

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

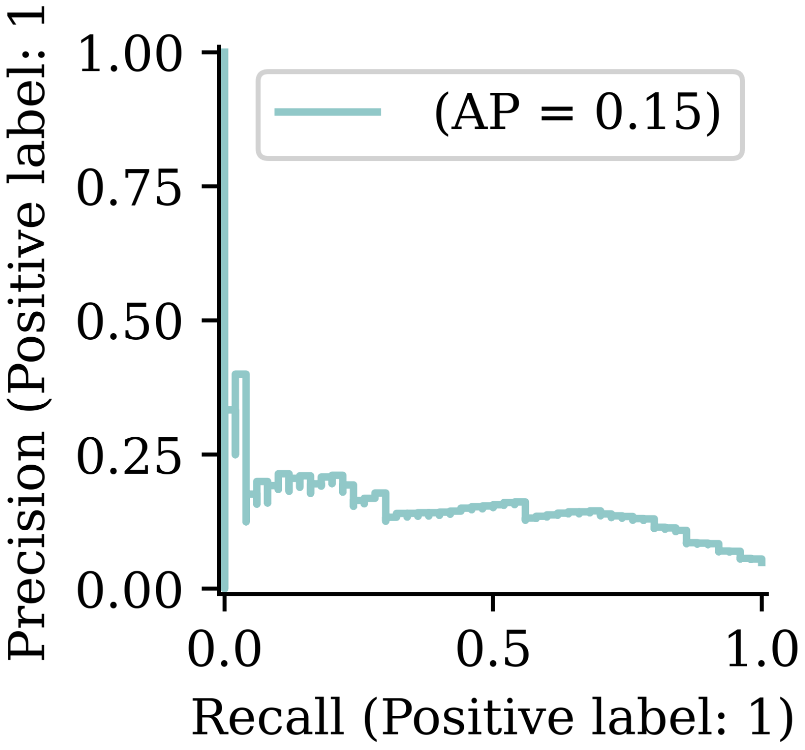
# Classification Metrics

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

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




```python
PrecisionRecallDisplay.from_predictions(y_test, y_pred, nar
```




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

```
array([[792, 180],
```

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

```
array([[662, 310],
```

# Package Versions

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

```
Python implementation: CPython
Python version       : 3.11.11
IPython version      : 8.32.0

keras     : 3.8.0
matplotlib: 3.10.0
numpy     : 1.26.4
pandas    : 2.2.3
seaborn   : 0.13.2
scipy     : 1.13.1
torch     : 2.5.1+cu124
tensorflow: 2.18.0
tf_keras  : 2.18.0
```

# Glossary

- accuracy
- classification problem
- confusion matrix
- cross-entropy loss
- metrics
- sigmoid activation function
- sofmax activation