# Categorical Variables

ACTL3143 & ACTL5111 Deep Learning for Actuaries
Patrick Laub





#### **Lecture Outline**

- Preprocessing
- French Motor Claims Dataset
- Ordinal Variables





#### Keras model methods

- compile: specify the loss function and optimiser
- fit: learn the parameters of the model
- predict: apply the model
- evaluate: apply the model and calculate a metric

```
random.seed(12)
model = Sequential()
model.add(Dense(1, activation="relu"))
model.compile("adam", "poisson")
model.fit(X_train, y_train, verbose=0)
y_pred = model.predict(X_val, verbose=0)
print(model.evaluate(X_val, y_val, verbose=0)
```

4.944334506988525





#### Scikit-learn model methods

- fit: learn the parameters of the model
- predict: apply the model
- score: apply the model and calculate a metric

```
1 model = LinearRegression()
2 model.fit(X_train, y_train)
3 y_pred = model.predict(X_val)
4 print(model.score(X_val, y_val))
```

-0.666850597951445





# Scikit-learn preprocessing methods

- fit: learn the parameters of the transformation
- transform: apply the transformation
- fit\_transform: learn the parameters and apply the transformation

```
fit | fit_transform
```

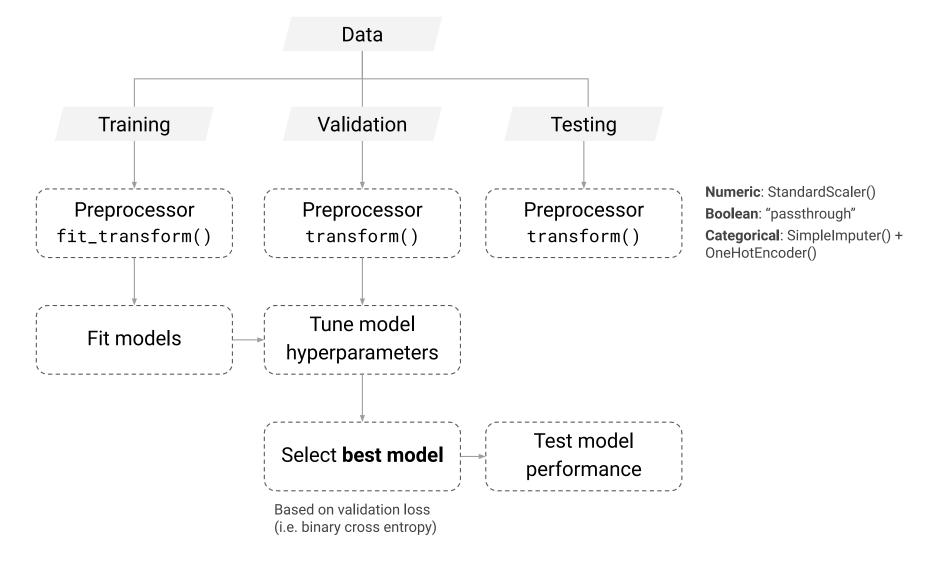
```
1 scaler = StandardScaler()
2 scaler.fit(X_train)
3 X_train_sc = scaler.transform(X_train)
4 X_val_sc = scaler.transform(X_val)
5 X_test_sc = scaler.transform(X_test)
6
7 print(X_train_sc.mean(axis=0))
8 print(X_train_sc.std(axis=0))
9 print(X_val_sc.mean(axis=0))
10 print(X_val_sc.std(axis=0))
11 2.97e-17 -2.18e-17 1.98e-17 -5.65e-17]
12 1. 1. 1.]
```

```
[ 2.97e-17 -2.18e-17 1.98e-17 -5.65e-17]
[1. 1. 1. 1.]
[-0.34 0.07 -0.27 -0.82]
[1.01 0.66 1.26 0.89]
```





# Summary of the splitting







# Dataframes & arrays

1	<pre>X_test.head(3)</pre>
---	---------------------------

	X1	<b>X2</b>	
83	0.075805	-0.677162	0.9751
53	0.954002	0.651391	-0.315
70	0.113517	0.662131	1.5860

```
1 X_test_sc
```

```
array([[ 0.13, -0.64, 0.89, -0.4 ],
      [1.15, 0.67, -0.44, 0.62],
      [0.18, 0.68, 1.52, -1.62],
      [0.77, -0.82, -1.22, 0.31],
      [0.06, 1.46, -0.39, 2.83],
      [2.21, 0.49, -1.34, 0.51],
      [-0.57, 0.53, -0.02, 0.86],
      [0.16, 0.61, -0.96, 2.12],
      [0.9, 0.2, -0.23, -0.57],
      [0.62, -0.11, 0.55, 1.48],
      [0., 1.57, -2.81, 0.69],
      [0.96, -0.87, 1.33, -1.81],
      [-0.64, 0.87, 0.25, -1.01],
      [-1.19, 0.49, -1.06, 1.51],
      [0.65, 1.54, -0.23, 0.22],
      [-1.13, 0.34, -1.05, -1.82],
      [0.02, 0.14, 1.2, -0.9],
      [0.68, -0.17, -0.34, 1.],
      [0.44, -1.72, 0.22, -0.66],
```



By default, when you pass sklearn a DataFrame it returns a numpy array.







# Keep as a DataFrame

#### From scikit-learn 1.2:

```
1 from sklearn import set_config
2 set_config(transform_output="pandas")
3
4 imp = SimpleImputer()
5 imp.fit(X_train)
6 X_train_imp = imp.fit_transform(X_train)
7 X_val_imp = imp.transform(X_val)
8 X_test_imp = imp.transform(X_test)
```

1 2	X_test_imp		
	X1	X2	
83	0.075805	-0.677162	O
53	0.954002	0.651391	_
•••	•••	•••	• •
42	-0.245388	-0.753736	_
69	0.199060	-0.600217	O
25 ro	ws × 4 colur	nns	





#### **Lecture Outline**

- Preprocessing
- French Motor Claims Dataset
- Ordinal Variables







#### French motor dataset

Download the dataset if we don't have it already.

```
from pathlib import Path
from sklearn.datasets import fetch_openml

if not Path("french-motor.csv").exists():
    freq = fetch_openml(data_id=41214, as_frame=True).frame
    freq.to_csv("french-motor.csv", index=False)

else:
    freq = pd.read_csv("french-motor.csv")

freq
```





# French motor dataset

	IDpol	ClaimNb	Exposure	Area	VehPower	VehA
O	1.0	1.0	0.10000	D	5.0	0.0
1	3.0	1.0	0.77000	D	5.0	0.0
2	5.0	1.0	0.75000	В	6.0	2.0
• • •	•••	•••	•••	• • •	•••	• • •
678010	6114328.0	0.0	0.00274	D	6.0	2.0
678011	6114329.0	0.0	0.00274	В	4.0	0.0
678012	6114330.0	0.0	0.00274	В	7.0	6.0

678013 rows × 12 columns





# Data dictionary

- IDpol: policy number (unique identifier)
- **ClaimNb**: number of claims on the given policy
- **Exposure**: total exposure in yearly units
- Area: area code (categorical, ordinal)
- VehPower: power of the car (categorical, ordinal)
- VehAge: age of the car in years
- DrivAge: age of the (most common) driver in years

- BonusMalus: bonus-malus level between 50 and 230 (with reference level 100)
- VehBrand: car brand (categorical, nominal)
- VehGas: diesel or regular fuel car (binary)
- Density: density of inhabitants per km<sup>2</sup> in the city of the living place of the driver
- Region: regions in France (prior to 2016)





#### The model

Have  $\{(\mathbf{x}_i, y_i)\}_{i=1,...,n}$  for  $\mathbf{x}_i \in \mathbb{R}^{47}$  and  $y_i \in \mathbb{N}_0$ .

Assume the distribution

$$Y_i \sim \mathsf{Poisson}(\lambda(\mathbf{x}_i))$$

We have  $\mathbb{E}Y_i = \lambda(\mathbf{x}_i)$ . The NN takes  $\mathbf{x}_i$  & predicts  $\mathbb{E}Y_i$ .





#### **Lecture Outline**

- Preprocessing
- French Motor Claims Dataset
- Ordinal Variables





# Subsample and split

```
freq = freq.drop("IDpol", axis=1).head(25_000)

X_train, X_test, y_train, y_test = train_test_split(
freq.drop("ClaimNb", axis=1), freq["ClaimNb"], random_state=2023)

# Reset each index to start at 0 again.
X_train = X_train.reset_index(drop=True)
X_test = X_test.reset_index(drop=True)
```



#### What values do we see in the data?

```
1 X_train["Area"].value_counts()
2 X_train["VehBrand"].value_counts()
3 X_train["VehGas"].value_counts()
4 X_train["Region"].value_counts()
```

```
VehBrand
Area
     5507
                                                   В1
                                                           5069
     4113
                                                   B2
                                                          4838
     3527
                                                   B12
                                                          3708
     2769
     2359
                                                           336
                                                   B13
      475
                                                   B11
                                                           284
Name: count, dtype: int64
                                                   B14
                                                           136
                                                   Name: count, Length: 11, dtype: int64
VehGas
                                                   Region
Regular
           10773
                                                   R24
                                                          6498
Diesel
            7977
                                                   R82
                                                          2119
Name: count, dtype: int64
                                                   R11
                                                          1909
                                                   R21
                                                            90
                                                   R42
                                                             55
                                                   R43
                                                             26
```

Name: count, Length: 22, dtype: int64



# Ordinal & binary categories are easy

```
1 from sklearn.preprocessing import OrdinalEncoder
  2 oe = OrdinalEncoder()
  3 oe.fit(X train[["Area", "VehGas"]])
  4 oe.categories
[array(['A', 'B', 'C', 'D', 'E', 'F'], dtype=object),
 array(['Diesel', 'Regular'], dtype=object)]
  1 for i, area in enumerate(oe.categories_[0]):
         print(f"The Area value {area} gets turned into {i}.")
The Area value A gets turned into 0.
The Area value B gets turned into 1.
The Area value C gets turned into 2.
The Area value D gets turned into 3.
The Area value E gets turned into 4.
The Area value F gets turned into 5.
  1 for i, gas in enumerate(oe.categories_[1]):
         print(f"The VehGas value {gas} gets turned into {i}.")
The VehGas value Diesel gets turned into 0.
The VehGas value Regular gets turned into 1.
```





### Ordinal encoded values

```
1 X_train_ord = oe.transform(X_train[["Area", "VehGas"]])
2 X_test_ord = oe.transform(X_test[["Area", "VehGas"]])
```

1 X\_train[["Area", "VehGas"]].head()

1 X\_train\_ord.head()

	Area	VehGas
0	C	Diesel
1	C	Regular
2	E	Regular
3	D	Diesel
4	A	Regular

	Area	VehGas
0	2.0	0.0
1	2.0	1.0
2	4.0	1.0
3	3.0	0.0
4	0.0	1.0





#### Train on ordinal encoded values

Epoch 22: early stopping 0.7821308970451355

What about adding the continuous variables back in? Use a sklearn *column transformer* for that.





# Preprocess ordinal & continuous

```
from sklearn.compose import make_column_transformer

ct = make_column_transformer(
    (OrdinalEncoder(), ["Area", "VehGas"]),
    ("drop", ["VehBrand", "Region"]),
    remainder=StandardScaler()

    )

X_train_ct = ct.fit_transform(X_train)
```

1 X\_train.head(3)

1 X\_train\_ct.head(3)

	Exposure	Area	VehPower		ordinalencoderArea	ord
0	1.00	C	6.0	О	2.0	0.0
1	0.36	C	4.0	1	2.0	1.0
2	0.02	E	12.0	2	4.0	1.0





# Preprocess ordinal & continuous II

```
from sklearn.compose import make_column_transformer

ct = make_column_transformer(
    (OrdinalEncoder(), ["Area", "VehGas"]),
    ("drop", ["VehBrand", "Region"]),
    remainder=StandardScaler(),
    verbose_feature_names_out=False
)

X_train_ct = ct.fit_transform(X_train)
```

1 X\_train.head(3)

1 X\_train\_ct.head(3)

	Exposure	Area	VehPower		Area	VehGas	Exposure
O	1.00	С	6.0	O	2.0	0.0	1.126979
1	0.36	C	4.0	1	2.0	1.0	-0.590896
2	0.02	E	12.0	2	4.0	1.0	-1.503517



