

Entity Embedding

ACTL3143 & ACTL5111 Deep Learning for Actuaries
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Lecture Outline

- Entity Embedding
- Categorical Variables & Entity Embeddings
- Keras' Functional API
- French Motor Dataset with Embeddings
- Scale By Exposure



Continuing on the French motor dataset example

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

```
1 from pathlib import Path
2 from sklearn.datasets import fetch_openml
3
4 if not Path("french-motor.csv").exists():
5     freq = fetch_openml(data_id=41214, as_frame=True).frame
6     freq.to_csv("french-motor.csv", index=False)
7 else:
8     freq = pd.read_csv("french-motor.csv")
9
10 freq
```



Source: Nell et al. (2020), [Case Study: French Motor Third-Party Liability Claims](#), SSRN.



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Continuing on the French motor dataset example

	IDpol	ClaimNb	Exposure	Area	VehPower	VehAge
0	1.0	1	0.10000	D	5	0
1	3.0	1	0.77000	D	5	0
...
678011	6114329.0	0	0.00274	B	4	0
678012	6114330.0	0	0.00274	B	7	6

678013 rows \times 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 km² in the city of the living place of the driver
- **Region**: regions in France (prior to 2016)



Source: Nell et al. (2020), **Case Study: French Motor Third-Party Liability Claims**, SSRN.



The model

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

Assume the distribution

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

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

 **Note**

For insurance, *this is a bit weird*. The exposures are different for each policy.

$\lambda(\mathbf{x}_i)$ is the expected number of claims for the duration of policy i 's contract.

Normally, $\text{Exposure}_i \notin \mathbf{x}_i$, and $\lambda(\mathbf{x}_i)$ is the expected rate *per year*, then

$$Y_i \sim \text{Poisson}(\text{Exposure}_i \times \lambda(\mathbf{x}_i)).$$



Where are things defined?

In Keras, string options are used for convenience to reference specific functions or settings.

```
1 model = Sequential([
2     Dense(30, activation="relu"),
3     Dense(1, activation="exponential")
4 ])
```

is the same as

```
1 from keras.activations import relu, exponential
2
3 model = Sequential([
4     Dense(30, activation=relu),
5     Dense(1, activation=exponential)
6 ])
```

```
1 x = [-1.0, 0.0, 1.0]
2 print(relu(x))
3 print(exponential(x))
```

```
tf.Tensor([0. 0. 1.], shape=(3,), dtype=float32)
tf.Tensor([0.37 1. 2.72], shape=(3,), dtype=float32)
```



String arguments to `.compile`

When we run

```
1 model.compile(optimizer="adam", loss="poisson")
```

it is equivalent to

```
1 from keras.losses import poisson
2 from keras.optimizers import Adam
3
4 model.compile(optimizer=Adam(), loss=poisson)
```

Why do this manually? To adjust the object:

```
1 optimizer = Adam(learning_rate=0.01)
2 model.compile(optimizer=optimizer, loss="poisson")
```

or to get help.



Keras' “poisson” loss

```
1 help(keras.losses.poisson)
```

Help on function poisson in module keras.src.losses.losses:

```
poisson(y_true, y_pred)
    Computes the Poisson loss between y_true and y_pred.
```

Formula:

```
```python
loss = y_pred - y_true * log(y_pred)
```
```

Args:

y_true: Ground truth values. shape = `batch_size, d0, .. dN`.

y_pred: The predicted values. shape = `batch_size, d0, .. dN`.

Returns:

Poisson loss values with shape = `batch_size, d0, .. dN-1`.



Subsample and split

```
1 freq = freq.drop("IDpol", axis=1).head(25_000)
2
3 X_train, X_test, y_train, y_test = train_test_split(
4     freq.drop("ClaimNb", axis=1), freq["ClaimNb"], random_state=2023)
5
6 # Reset each index to start at 0 again.
7 X_train = X_train.reset_index(drop=True)
8 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()
```

Area

C 5507
D 4113

...

B 2359
F 475

Name: count, Length: 6, dtype: int64

VehGas

'Regular' 10773
'Diesel' 7977
Name: count, dtype: int64

VehBrand

B1 5069
B2 4838

...

B11 284
B14 136

Name: count, Length: 11, dtype: int64

Region

R24 6498
R82 2119

...

R42 55
R43 26

Name: count, Length: 22, dtype: int64



Preprocess ordinal & continuous

```

1 from sklearn.compose import make_column_transformer
2
3 ct = make_column_transformer(
4     (OrdinalEncoder(), ["Area", "VehGas"]),
5     ("drop", ["VehBrand", "Region"]),
6     remainder=StandardScaler(),
7     verbose_feature_names_out=False
8 )
9 X_train_ct = ct.fit_transform(X_train)

```

1 X_train.head(3)

| | Exposure | Area | VehPower |
|---|-----------------|-------------|-----------------|
| 0 | 1.00 | C | 6 |
| 1 | 0.36 | C | 4 |
| 2 | 0.02 | E | 12 |

1 X_train_ct.head(3)

| | Area | VehGas | Exposure | VehPower |
|---|-------------|---------------|-----------------|-----------------|
| 0 | 2.0 | 0.0 | 1.126979 | - |
| 1 | 2.0 | 1.0 | -0.590896 | - |
| 2 | 4.0 | 1.0 | -1.503517 | 3 |

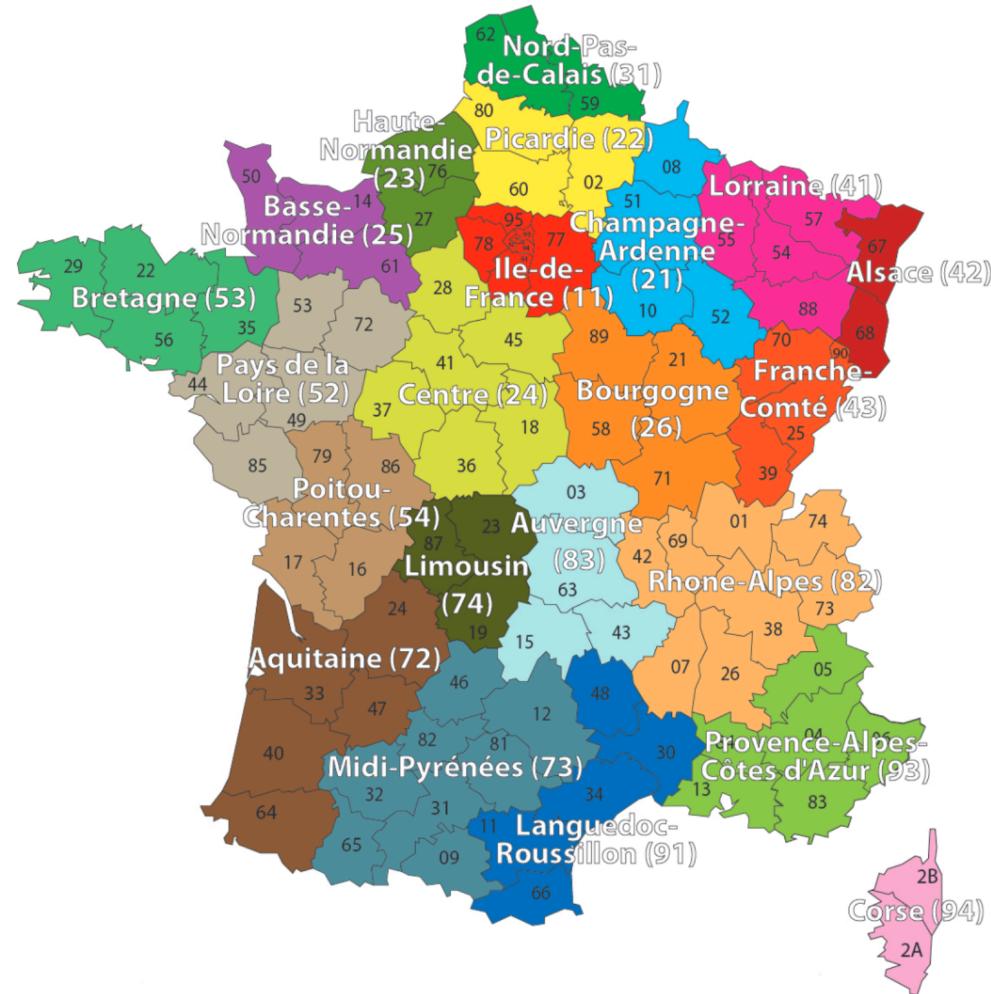


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Region column



French Administrative Regions



Source: Nell et al. (2020), Case Study: French Motor Third-Party Liability Claims, SSRN.

One-hot encoding

```

1 oe = OneHotEncoder(sparse_output=False)
2 X_train_oh = oe.fit_transform(X_train[["Region"]])
3 X_test_oh = oe.transform(X_test[["Region"]])
4 print(list(X_train["Region"][:5]))
5 X_train_oh.head()

```

['R24', 'R93', 'R11', 'R42', 'R24']

| | Region_R11 | Region_R21 | Region_R22 | Region_R23 | Region |
|-----|-------------------|-------------------|-------------------|-------------------|---------------|
| 0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| 1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| ... | ... | ... | ... | ... | ... |
| 3 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 4 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |

5 rows × 22 columns



Train on one-hot inputs

```
1 num_regions = len(oe.categories_[0])
2
3 random.seed(12)
4 model = Sequential([
5     Dense(2, input_dim=num_regions),
6     Dense(1, activation="exponential")
7 ])
8
9 model.compile(optimizer="adam", loss="poisson")
10
11 es = EarlyStopping(verbose=True)
12 hist = model.fit(X_train_oh, y_train, epochs=100, verbose=0,
13     validation_split=0.2, callbacks=[es])
14 hist.history["val_loss"][-1]
```

Epoch 12: early stopping

0.7526934146881104



Consider the first layer

```
1 every_category = pd.DataFrame(np.eye(num_regions), columns=oe.categories_[0])
2 every_category.head(3)
```

| | R11 | R21 | R22 | R23 | R24 | R25 | R26 | R31 | R41 | R42 | ... | R53 | R54 | R72 | R73 | R74 | R8 |
|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 1 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 2 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

3 rows × 22 columns

```
1 # Put this through the first layer of the model
2 X = every_category.to_numpy()
3 model.layers[0](X)
```

```
<tf.Tensor: shape=(22, 2), dtype=float32, numpy=
array([[-0.21, -0.14],
       [ 0.21, -0.17],
       [-0.22,  0.1 ],
       [-0.83,  0.1 ],
       [-0.01, -0.66],
       [-0.65, -0.13],
       [-0.36, -0.41],
       [ 0.21, -0.03],
       [-0.93, -0.57],
       [ 0.2 , -0.41],
       [-0.43, -0.21],
       [-1.13, -0.33],
       [ 0.17, -0.68],
       [-0.88, -0.55],
       [-0.13,  0.05],
       [ 0.11,  0. ],
       [-0.46, -0.38],
       [-0.62, -0.37],
       [-0.19, -0.28]].
```



The first layer

```
1 layer = model.layers[0]
2 W, b = layer.get_weights()
3 X.shape, W.shape, b.shape
```

((22, 22), (22, 2), (2,))

1 $X @ W + b$

```
array([[-0.21, -0.14],
       [ 0.21, -0.17],
       [-0.22,  0.1 ],
       [-0.83,  0.1 ],
       [-0.01, -0.66],
       [-0.65, -0.13],
       [-0.36, -0.41],
       [ 0.21, -0.03],
       [-0.93, -0.57],
       [ 0.2 , -0.41],
       [-0.43, -0.21],
       [-1.13, -0.33],
       [ 0.17, -0.68],
       [-0.88, -0.55],
       [-0.13,  0.05],
       [ 0.11,  0. ],
       [-0.46, -0.38],
       [-0.62, -0.37],
```

1 $W + b$

```
array([[-0.21, -0.14],
       [ 0.21, -0.17],
       [-0.22,  0.1 ],
       [-0.83,  0.1 ],
       [-0.01, -0.66],
       [-0.65, -0.13],
       [-0.36, -0.41],
       [ 0.21, -0.03],
       [-0.93, -0.57],
       [ 0.2 , -0.41],
       [-0.43, -0.21],
       [-1.13, -0.33],
       [ 0.17, -0.68],
       [-0.88, -0.55],
       [-0.13,  0.05],
       [ 0.11,  0. ],
       [-0.46, -0.38],
       [-0.62, -0.37],
```



Just a look-up operation

```
1 display(list(oe.categories_[0]))
```

```
['R11',
 'R21',
 'R22',
 'R23',
 'R24',
 'R25',
 'R26',
 'R31',
 'R41',
 'R42',
 'R43',
 'R52',
 'R53',
 'R54',
 'R72',
 'R73',
 'R74',
 'R82'].
```

```
1 W + b
```

```
array([[-0.21, -0.14],
       [ 0.21, -0.17],
       [-0.22,  0.1 ],
       [-0.83,  0.1 ],
       [-0.01, -0.66],
       [-0.65, -0.13],
       [-0.36, -0.41],
       [ 0.21, -0.03],
       [-0.93, -0.57],
       [ 0.2 , -0.41],
       [-0.43, -0.21],
       [-1.13, -0.33],
       [ 0.17, -0.68],
       [-0.88, -0.55],
       [-0.13,  0.05],
       [ 0.11,  0. ],
       [-0.46, -0.38],
       [-0.62, -0.37].
```



Turn the region into an index

```
1 oe = OrdinalEncoder()
2 X_train_reg = oe.fit_transform(X_train[["Region"]])
3 X_test_reg = oe.transform(X_test[["Region"]])
4
5 for i, reg in enumerate(oe.categories_[0][:3]):
6     print(f"The Region value {reg} gets turned into {i}.")
```

The Region value R11 gets turned into 0.

The Region value R21 gets turned into 1.

The Region value R22 gets turned into 2.



Embedding

```
1 from keras.layers import Embedding
2 num_regions = len(np.unique(X_train[["Region"]]))
3
4 random.seed(12)
5 model = Sequential([
6     Embedding(input_dim=num_regions, output_dim=2),
7     Dense(1, activation="exponential")
8 ])
9
10 model.compile(optimizer="adam", loss="poisson")
```



Fitting that model

```
1 es = EarlyStopping(verbose=True)
2 hist = model.fit(X_train_reg, y_train, epochs=100, verbose=0,
3                   validation_split=0.2, callbacks=[es])
4 hist.history["val_loss"][-1]
```

Epoch 5: early stopping

0.7526668906211853

```
1 model.layers
```

[<Embedding name=embedding, built=True>, <Dense name=dense_6, built=True>]



Keras' Embedding Layer

```
1 model.layers[0].get_weights()[0]
```

```
array([[-0.12, -0.11],
       [ 0.03, -0. ],
       [-0.02,  0.01],
       [-0.25, -0.14],
       [-0.28, -0.32],
       [-0.3 , -0.22],
       [-0.31, -0.28],
       [ 0.1 ,  0.07],
       [-0.61, -0.51],
       [-0.06, -0.12],
       [-0.17, -0.14],
       [-0.6 , -0.46],
       [-0.22, -0.27],
       [-0.59, -0.5 ],
       [-0. ,  0.02],
       [ 0.07,  0.06],
       [-0.31, -0.28],
       [-0.4 , -0.34].
```

```
1 X_train["Region"].head(4)
```

```
0    R24
1    R93
2    R11
3    R42
Name: Region, dtype: object
```

```
1 X_sample = X_train_reg[:4].to_numpy()
2 X_sample
```

```
array([[ 4.],
       [20.],
       [ 0.],
       [ 9.]])
```

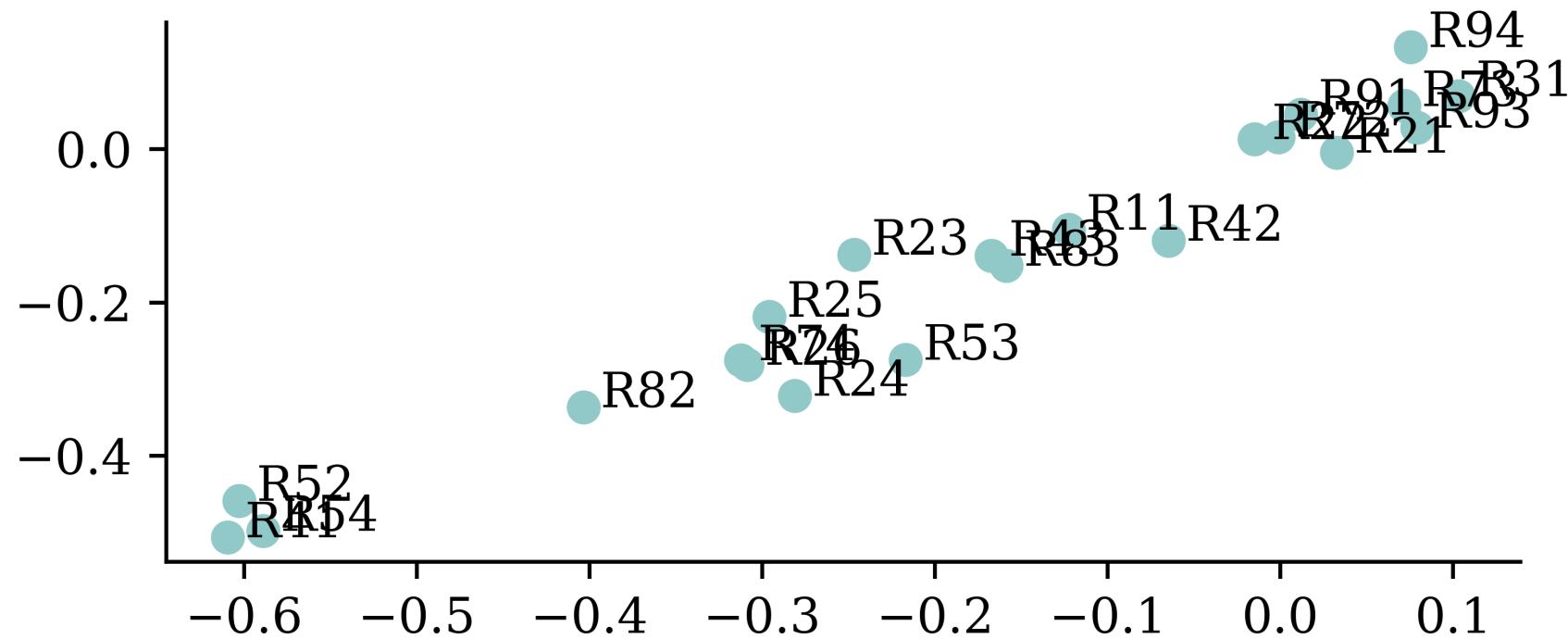
```
1 enc_tensor = model.layers[0](X_sample)
2 keras.ops.convert_to_numpy(enc_tensor).s
```

```
array([[-0.28, -0.32],
       [ 0.08,  0.03],
       [-0.12, -0.11],
       [-0.06, -0.12]], dtype=float32)
```

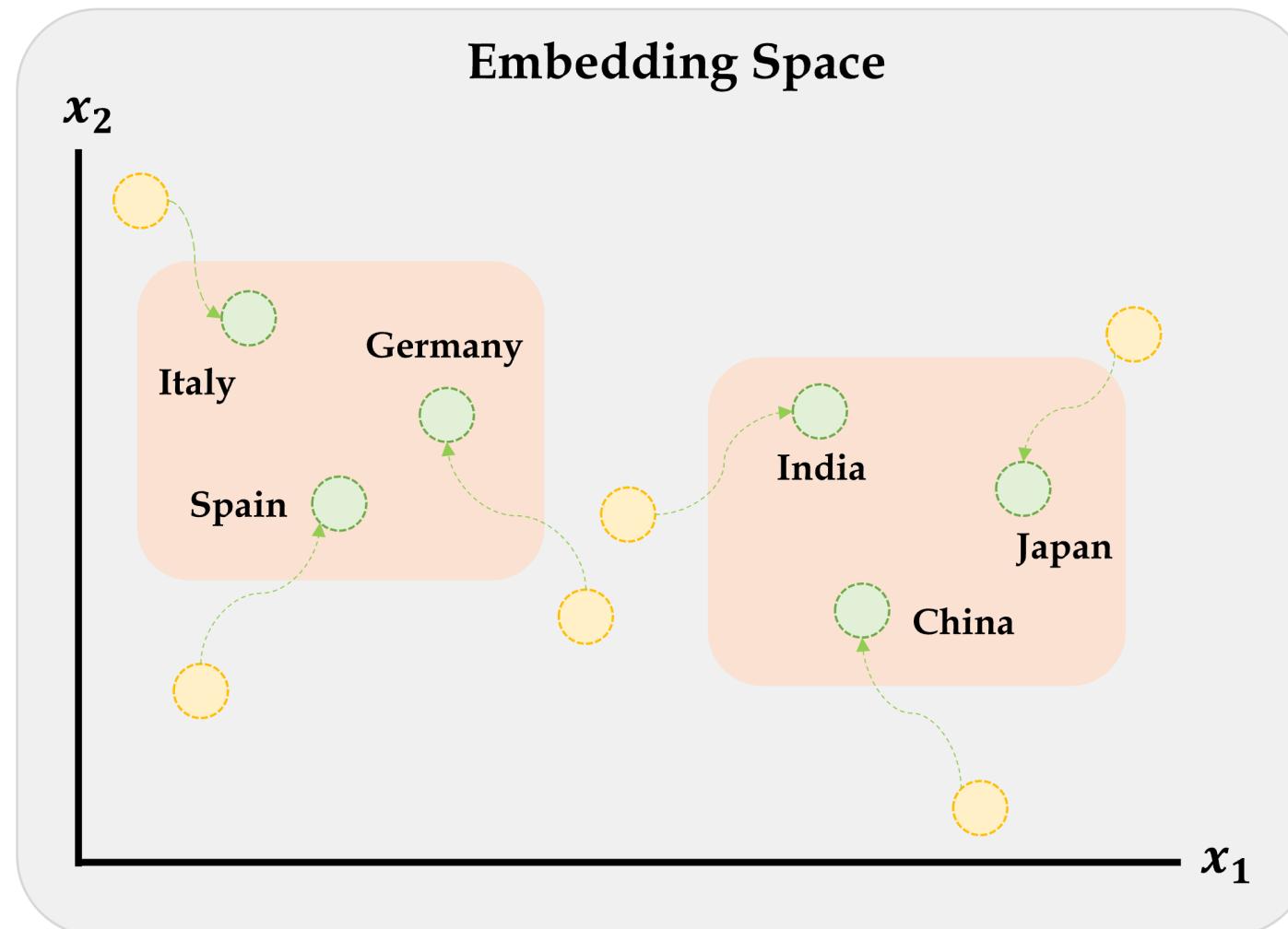


The learned embeddings

```
1 points = model.layers[0].get_weights()[0]
2 plt.scatter(points[:,0], points[:,1])
3 for i in range(num_regions):
4     plt.text(points[i,0]+0.01, points[i,1] , s=oe.categories_[0][i])
```



Entity embeddings



Entity embeddings will gradually improve during training.

Source: Marcus Lautier (2022).



Embeddings & other inputs

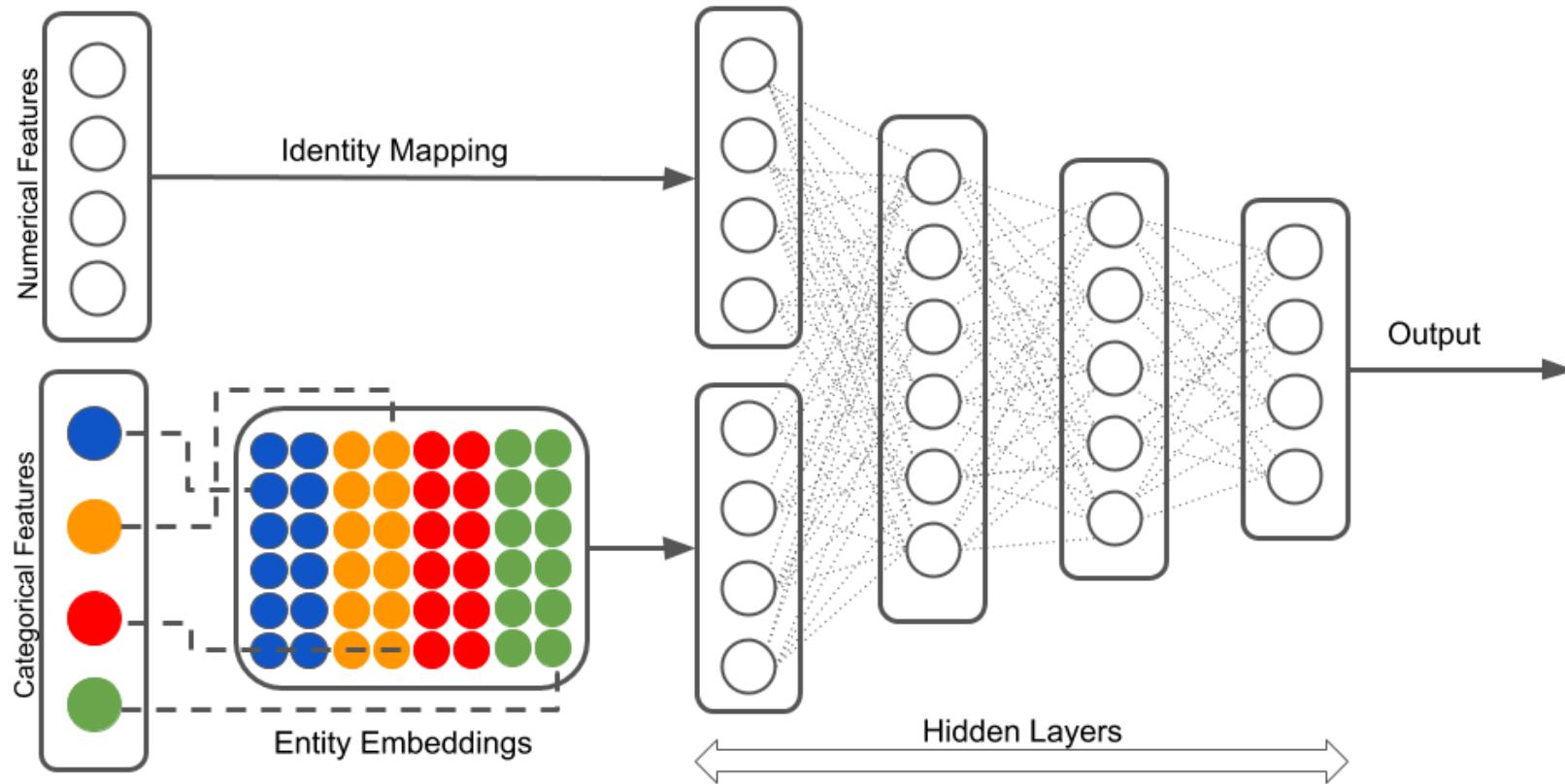


Illustration of a neural network with both continuous and categorical inputs.

We can't do this with Sequential models...



Source: LotusLabs Blog, [Accurate insurance claims prediction with Deep Learning](#).



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- French Motor Dataset with Embeddings
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Converting Sequential models

```
1 from keras.models import Model
2 from keras.layers import Input
```

```
1 random.seed(12)
2
3 model = Sequential([
4     Dense(30, "leaky_relu"),
5     Dense(1, "exponential")
6 ])
7
8 model.compile(
9     optimizer="adam",
10    loss="poisson")
11
12 hist = model.fit(
13     X_train_oh, y_train,
14     epochs=1, verbose=0,
15     validation_split=0.2)
16 hist.history["val_loss"][-1]
```

0.7535399198532104

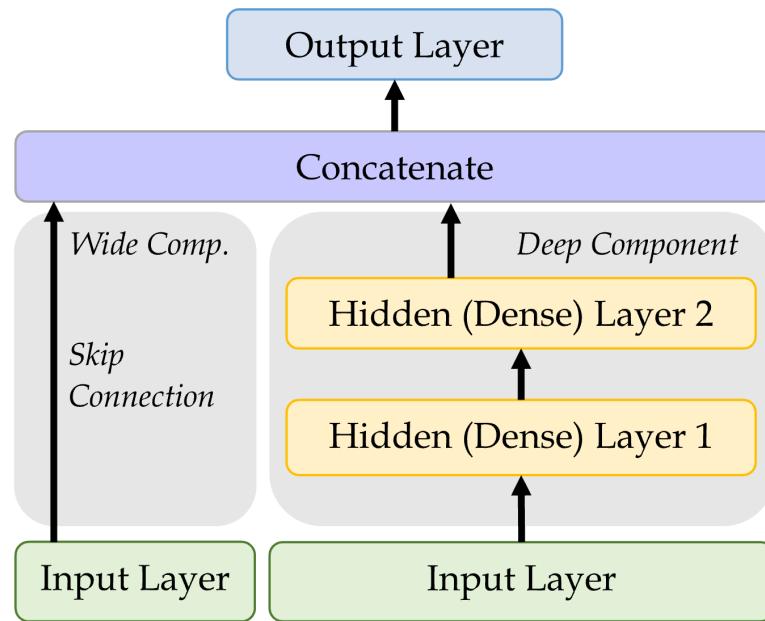
```
1 random.seed(12)
2
3 inputs = Input(shape=(X_train_oh.shape[1]
4 x = Dense(30, "leaky_relu")(inputs)
5 out = Dense(1, "exponential")(x)
6 model = Model(inputs, out)
7
8 model.compile(
9     optimizer="adam",
10    loss="poisson")
11
12 hist = model.fit(
13     X_train_oh, y_train,
14     epochs=1, verbose=0,
15     validation_split=0.2)
16 hist.history["val_loss"][-1]
```

0.7535399198532104

See one-length tuples.



Wide & Deep network



An illustration of the wide & deep network architecture.

Add a *skip connection* from input to output layers.

```

1 from keras.layers \
2     import Concatenate
3
4 inp = Input(shape=X_train.shape[1:])
5 hidden1 = Dense(30, "leaky_relu")(inp)
6 hidden2 = Dense(30, "leaky_relu")(hidden1)
7 concat = Concatenate()(
8     [inp, hidden2])
9 output = Dense(1)(concat)
10 model = Model(
11     inputs=[inp],
12     outputs=[output])
  
```



Naming the layers

For complex networks, it is often useful to give meaningful names to the layers.

```
1 input_ = Input(shape=X_train.shape[1:], name="input")
2 hidden1 = Dense(30, activation="leaky_relu", name="hidden1")(input_)
3 hidden2 = Dense(30, activation="leaky_relu", name="hidden2")(hidden1)
4 concat = Concatenate(name="combined")([input_, hidden2])
5 output = Dense(1, name="output")(concat)
6 model = Model(inputs=[input_], outputs=[output])
```

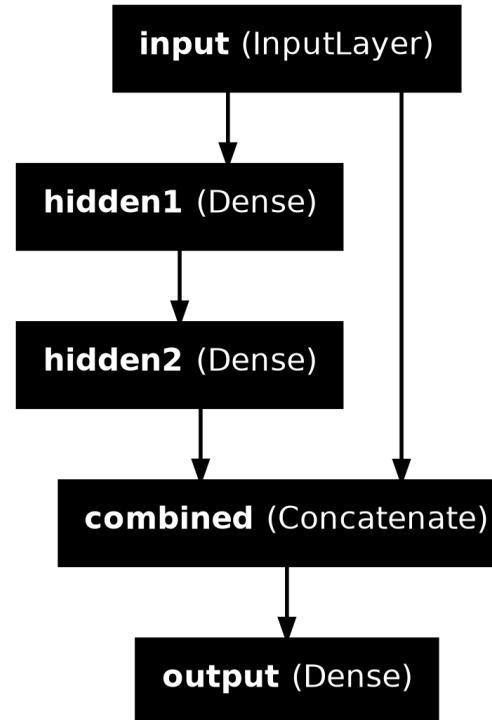


Inspecting a complex model

```
1 from keras.utils import plot_model
```

```
1 plot_model(model, sho
```

```
1 model.summary(line_length=75)
```



Model: "functional_5"

| Layer (type) | Output Shape | Param # | Connected |
|------------------------|--------------|---------|-------------------------|
| input (InputLayer) | (None, 10) | 0 | - |
| hidden1 (Dense) | (None, 30) | 330 | input[0][0] |
| hidden2 (Dense) | (None, 30) | 930 | hidden1[0] |
| combined (Concatenate) | (None, 40) | 0 | input[0][0], hidden2[0] |
| output (Dense) | (None, 1) | 41 | combined[0] |

Total params: 1,301 (5.08 KB)

Trainable params: 1,301 (5.08 KB)

Non-trainable params: 0 (0.00 B)



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The desired architecture

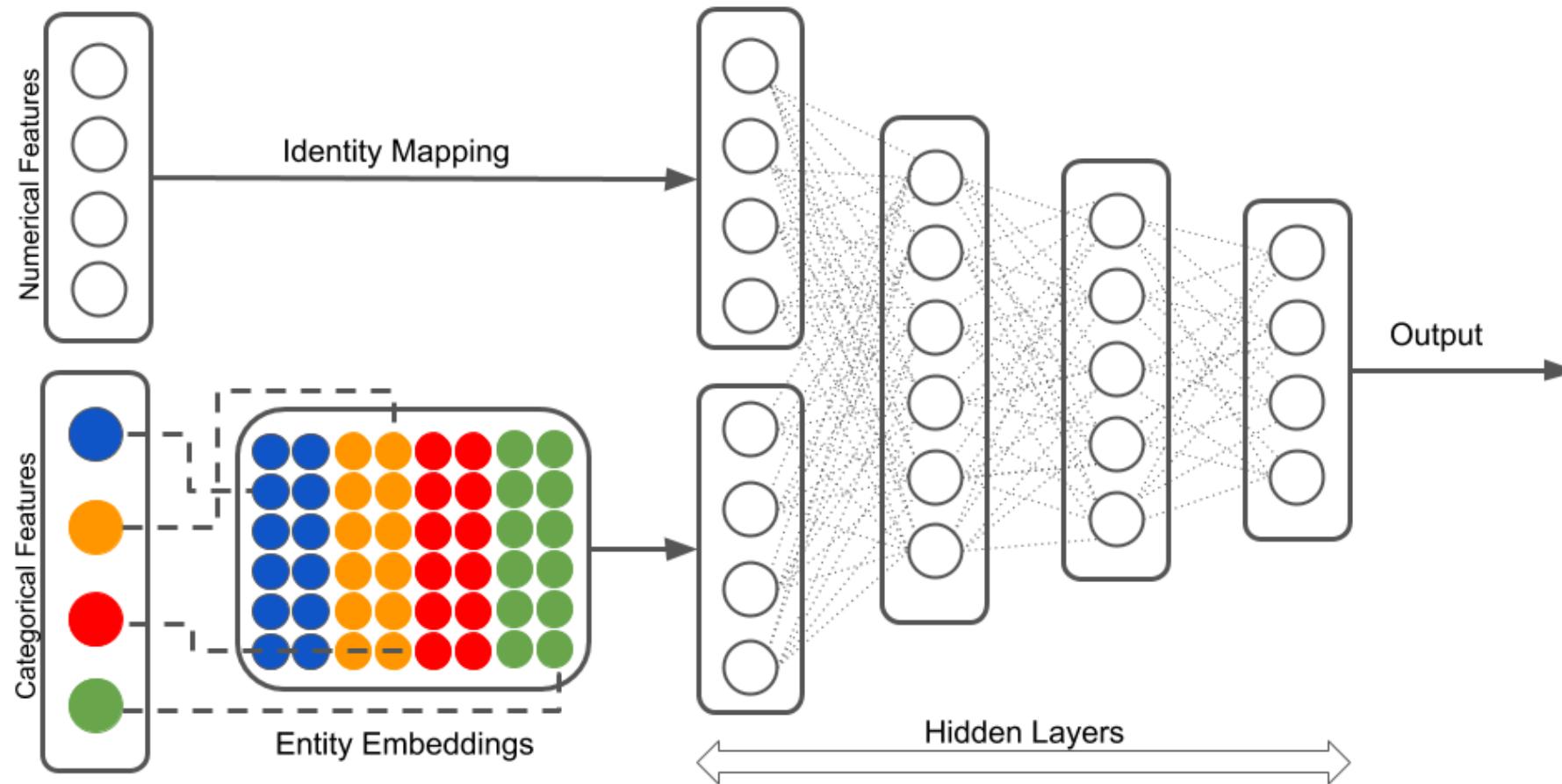


Illustration of a neural network with both continuous and categorical inputs.



Source: LotusLabs Blog, [Accurate insurance claims prediction with Deep Learning](#).



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Preprocess all French motor inputs

Transform the categorical variables to integers:

```
1 num_brands, num_regions = X_train.nunique()[["VehBrand", "Region"]]  
2  
3 ct = make_column_transformer(  
4     (OrdinalEncoder(), ["VehBrand", "Region", "Area", "VehGas"]),
5     remainder=StandardScaler(),
6     verbose_feature_names_out=False
7 )
8 X_train_ct = ct.fit_transform(X_train)
9 X_test_ct = ct.transform(X_test)
```

Split the brand and region data apart from the rest:

```
1 X_train_brand = X_train_ct["VehBrand"]; X_test_brand = X_test_ct["VehBrand"]
2 X_train_region = X_train_ct["Region"]; X_test_region = X_test_ct["Region"]
3 X_train_rest = X_train_ct.drop(["VehBrand", "Region"], axis=1)
4 X_test_rest = X_test_ct.drop(["VehBrand", "Region"], axis=1)
```



Organise the inputs

Make a Keras [Input](#) for: vehicle brand, region, & others.

```
1 veh_brand = Input(shape=(1,), name="vehBrand")
2 region = Input(shape=(1,), name="region")
3 other_inputs = Input(shape=X_train_rest.shape[1:], name="otherInputs")
```

Create embeddings and join them with the other inputs.

```
1 from keras.layers import Reshape
2
3 random.seed(1337)
4 veh_brand_ee = Embedding(input_dim=num_brands, output_dim=2,
5     name="vehBrandEE")(veh_brand)
6 veh_brand_ee = Reshape(target_shape=(2,))(veh_brand_ee)
7
8 region_ee = Embedding(input_dim=num_regions, output_dim=2,
9     name="regionEE")(region)
10 region_ee = Reshape(target_shape=(2,))(region_ee)
11
12 x = Concatenate(name="combined")([veh_brand_ee, region_ee, other_inputs])
```



Complete the model and fit it

Feed the combined embeddings & continuous inputs to some normal dense layers.

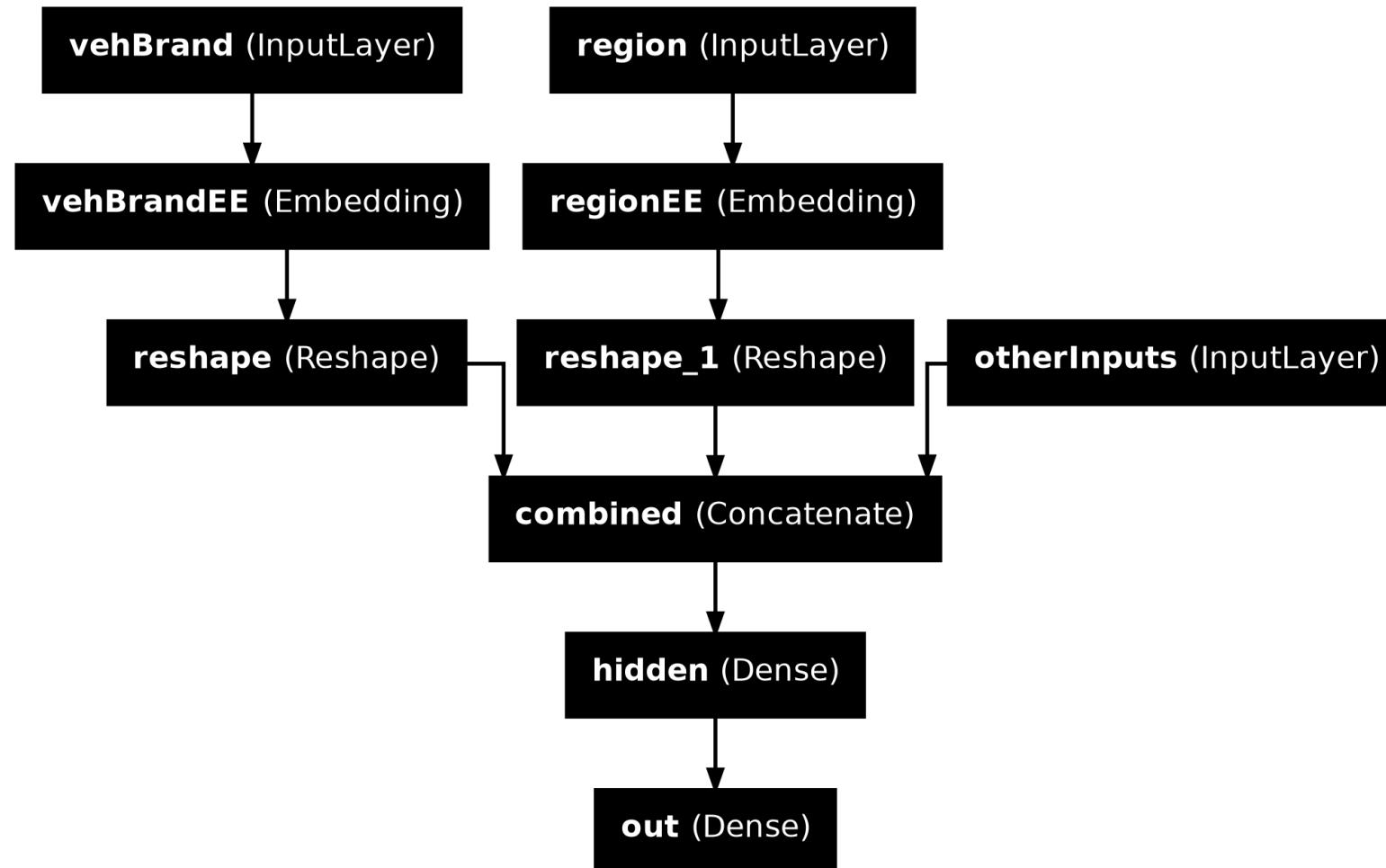
```
1 x = Dense(30, "relu", name="hidden")(x)
2 out = Dense(1, "exponential", name="out")(x)
3
4 model = Model([veh_brand, region, other_inputs], out)
5 model.compile(optimizer="adam", loss="poisson")
6
7 hist = model.fit((X_train_brand, X_train_region, X_train_rest),
8      y_train, epochs=100, verbose=0,
9      callbacks=[EarlyStopping(patience=5)], validation_split=0.2)
10 np.min(hist.history["val_loss"])
```

0.6692776679992676



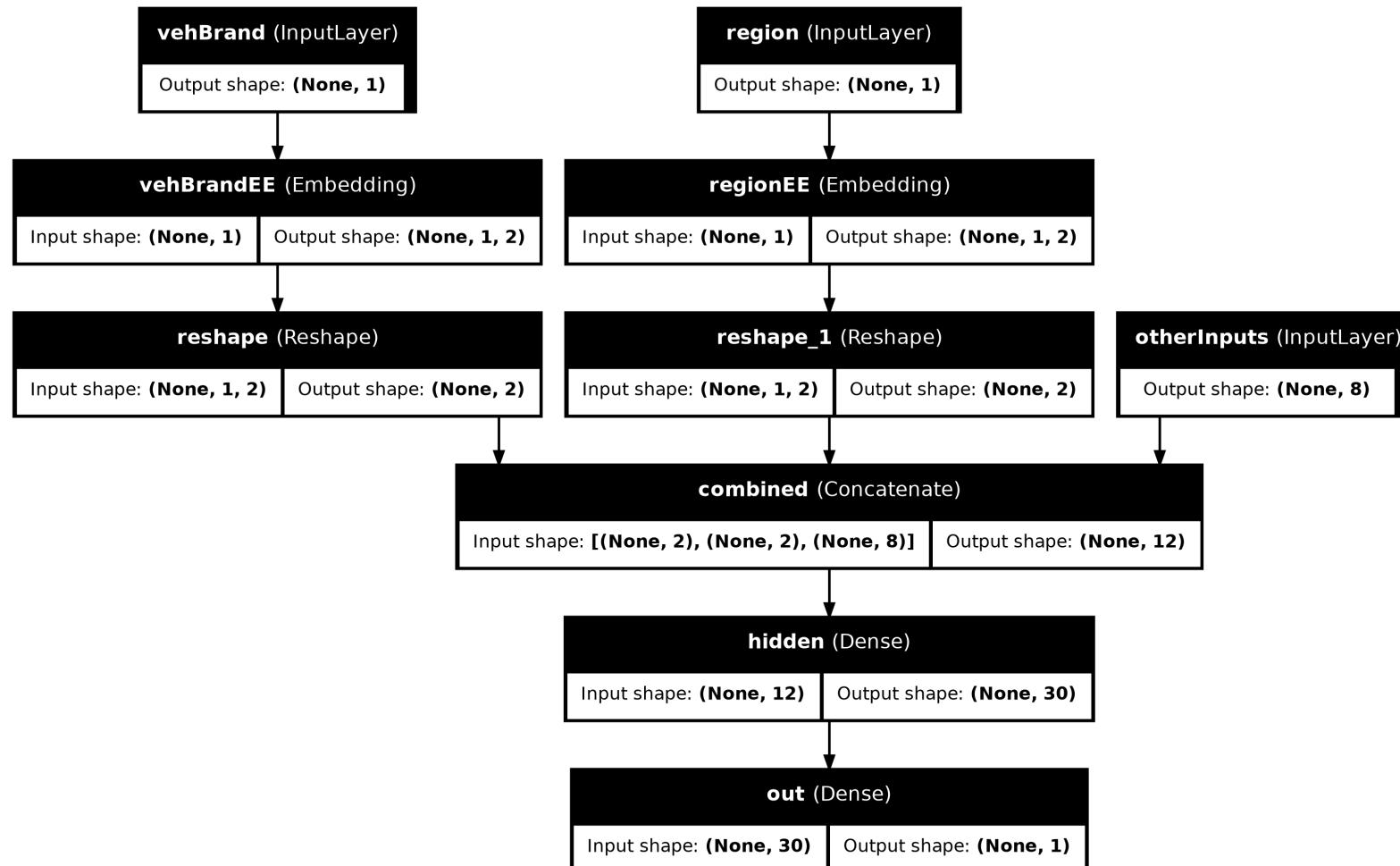
Plotting this model

```
1 plot_model(model, show_layer_names=True)
```



Why we need to reshape

```
1 plot_model(model, show_layer_names=True, show_shapes=True)
```



Lecture Outline

- Entity Embedding
- Categorical Variables & Entity Embeddings
- Keras' Functional API
- French Motor Dataset with Embeddings
- **Scale By Exposure**



Two different models

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

Model 1: Say $Y_i \sim \text{Poisson}(\lambda(\mathbf{x}_i))$.

But, the exposures are different for each policy. $\lambda(\mathbf{x}_i)$ is the expected number of claims for the duration of policy i 's contract.

Model 2: Say $Y_i \sim \text{Poisson}(\text{Exposure}_i \times \lambda(\mathbf{x}_i))$.

Now, $\text{Exposure}_i \notin \mathbf{x}_i$, and $\lambda(\mathbf{x}_i)$ is the rate *per year*.



Just take continuous variables

```

1 ct = make_column_transformer(
2     ("passthrough", ["Exposure"]),
3     ("drop", ["VehBrand", "Region", "Area", "VehGas"]),
4     remainder=StandardScaler(),
5     verbose_feature_names_out=False
6 )
7 X_train_ct = ct.fit_transform(X_train)
8 X_test_ct = ct.transform(X_test)

```

Split exposure apart from the rest:

```

1 X_train_exp = X_train_ct["Exposure"]; X_test_exp = X_test_ct["Exposure"]
2 X_train_rest = X_train_ct.drop("Exposure", axis=1)
3 X_test_rest = X_test_ct.drop("Exposure", axis=1)

```

Organise the inputs:

```

1 exposure = Input(shape=(1,), name="exposure")
2 other_inputs = Input(shape=X_train_rest.shape[1:], name="otherInputs")

```



Make & fit the model

Feed the continuous inputs to some normal dense layers.

```
1 random.seed(1337)
2 x = Dense(30, "relu", name="hidden1")(other_inputs)
3 x = Dense(30, "relu", name="hidden2")(x)
4 lambda_ = Dense(1, "exponential", name="lambda")(x)

1 out = lambda_ * exposure # In past, need keras.layers.Multiply()(lambda_, exposure]
2 model = Model([exposure, other_inputs], out)
3 model.compile(optimizer="adam", loss="poisson")
4
5 es = EarlyStopping(patience=10, restore_best_weights=True, verbose=1)
6 hist = model.fit((X_train_exp, X_train_rest),
7     y_train, epochs=100, verbose=0,
8     callbacks=[es], validation_split=0.2)
9 np.min(hist.history["val_loss"])
```

Epoch 37: early stopping

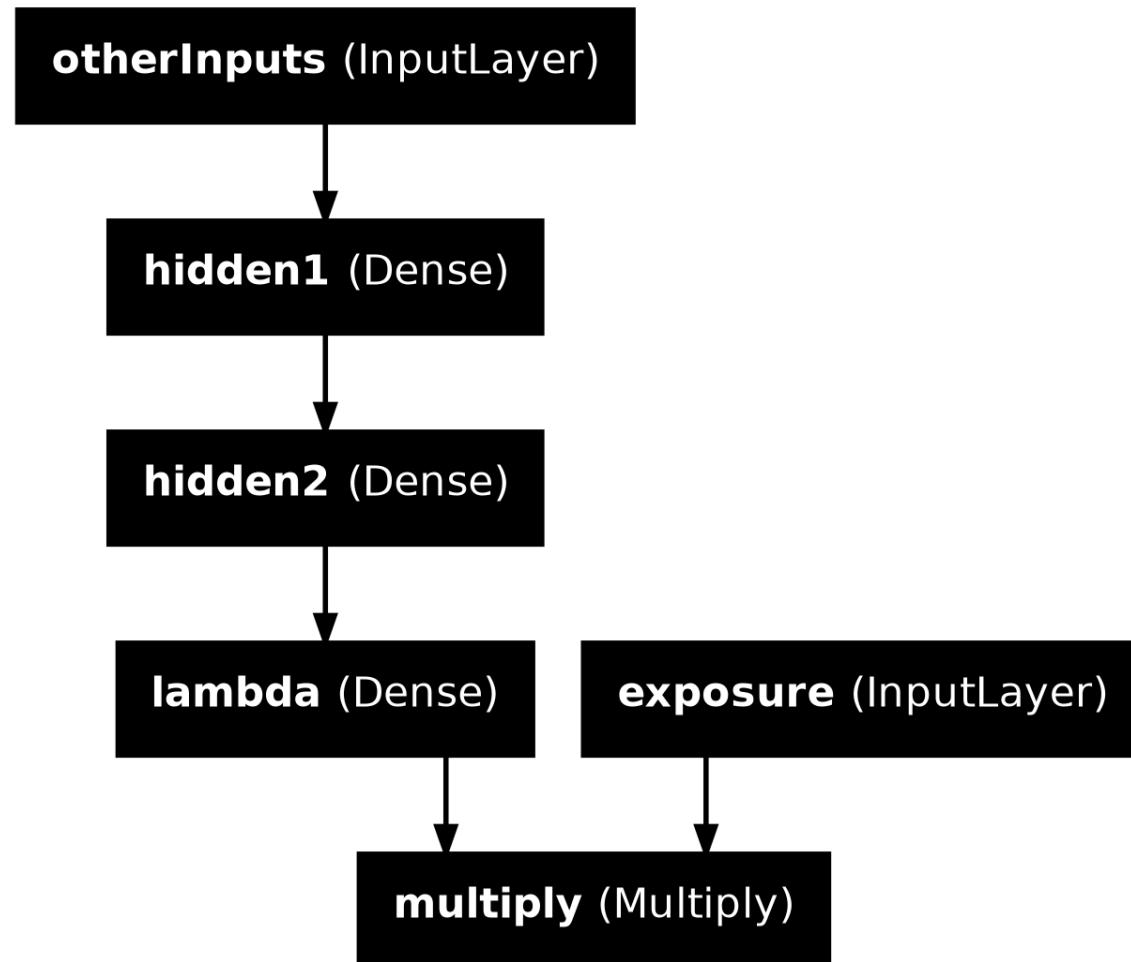
Restoring model weights from the end of the best epoch: 27.

0.8828736543655396



Plot the model

```
1 plot_model(model, show_layer_names=True)
```



Package Versions

```
1 from watermark import watermark  
2 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

- entity embeddings
- Input layer
- Keras functional API
- Reshape layer
- skip connection
- wide & deep network

