Bridging the pandas — scikit-learn dtype divide

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The Problem

Two Data Models

| | Broadcast- ing | Vectorization | ufuncs | typed arrays | ND-arrays | Labels | Heterogeneous | Extension dtypes |
|-----------------------------|-------------------|---------------|--------|--------------|-----------|--------|---------------|-------------------------|
| scikit- learn / NumPy | | | | | | | | |
| Pandas | | | | | | | | |

Two Data Models

Claim: "Real world" data are

- Labeled
- Heterogenous
- Messy

The Data

```
In [1]: import numpy as np
   ...: import pandas as pd
   ...: import seaborn as sns
   • • • •
   ...: tips = pd.read_csv('tips.csv')
   ...: tips.head()
   • • • •
Out[1]:
   total_bill
              tip
                    sex smoker
                                    day
                                          time
                                                size
                    Female
        16.99
              1.01
                               No
                                   Sun
                                         Dinner
        10.34
              1.66
                     Male
                               No Sun
                                         Dinner
        21.01
              3.50
                      Male
                                No
                                   Sun
                                         Dinner
        23.68
              3.31
                                         Dinner
                     Male
                                No
                                   Sun
        24.59
              3.61
                    Female
                                No
                                   Sun
                                         Dinner
```

The Data

```
In [2]: tips.info()
Out[2]:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 7 columns):
total_bill 244 non-null float64
            244 non-null float64
tip
            244 non-null object
sex
smoker
            244 non-null object
             244 non-null object
day
time
             244 non-null object
size
             244 non-null int64
dtypes: float64(2), int64(1), object(4)
memory usage: 13.4+ KB
```

```
In [3]: X = tips.drop("tip", axis=1)
...: y = tips["tip"]
```

The Stats

The Statistics: linear model

```
>>> model = LinearRegression()
>>> model.fit(X, y)
```

The Statistics: linear model

```
>>> model = LinearRegression()
>>> model.fit(X, y)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
  File "sklearn/linear_model/base.py", line 427, in fit
   y_numeric=True, multi_output=True)
  File "sklearn/utils/validation.py", line 510, in check_X_y
   ensure_min_features, warn_on_dtype, estimator)
 File "sklearn/utils/validation.py", line 393, in check_array
   array = array.astype(np.float64)
ValueError: could not convert string to float: 'Dinner'
```

The Statistics: linear model

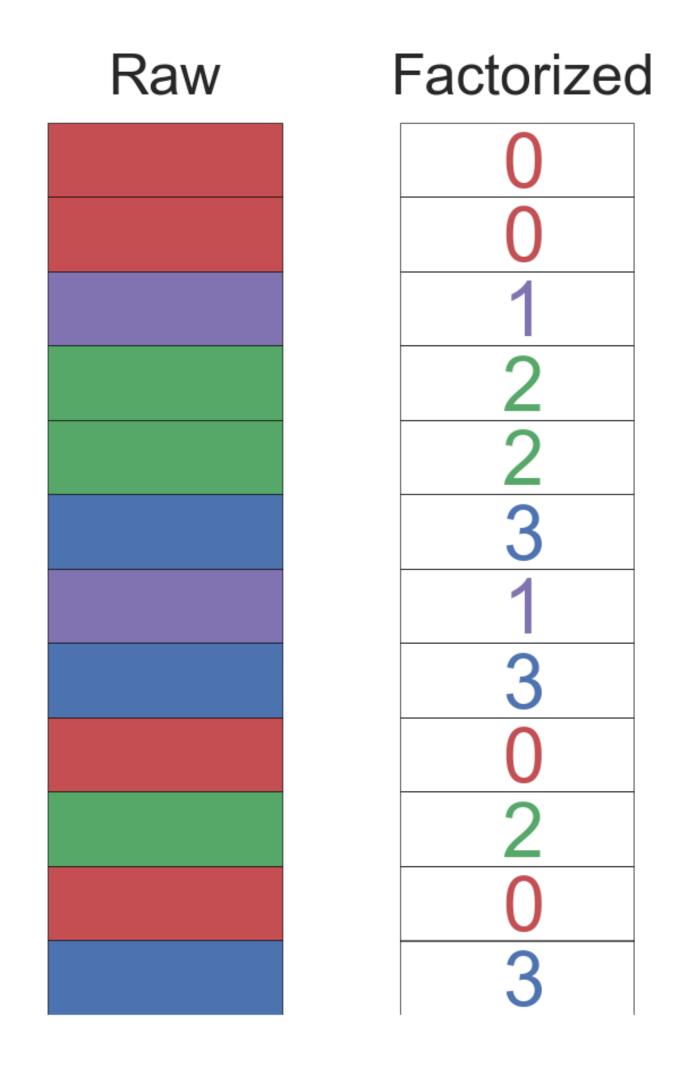
```
>>> model = LinearRegression()
>>> model.fit(X, y)
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 File "sklearn/utils/validation.py", line 393, in check_array
   array = array.astype(np.float64)
ValueError: could not convert string to float: 'Dinner'
```

$$oldsymbol{y} = oldsymbol{X}oldsymbol{eta} + oldsymbol{arepsilon} \ \hat{oldsymbol{eta}} = \left(oldsymbol{X}^Toldsymbol{X}^Toldsymbol{X}
ight)^{-1}oldsymbol{X}^Toldsymbol{y}$$

Aside: R vs. Python

```
> lm(tip ~ ., tips)
Call:
lm(formula = tip \sim ., data = tips)
Coefficients:
              total_bill
                                         smokerYes
                                                                       daySun
(Intercept)
                              sexMale
                                                         daySat
   0.80382
                 0.09449
                                          -0.08641
                                                       -0.12146
                                                                     -0.02548
                             -0.03244
              timeLunch
   dayThur
                                 size
   -0.16226
                 0.06813
                              0.17599
```

transformations

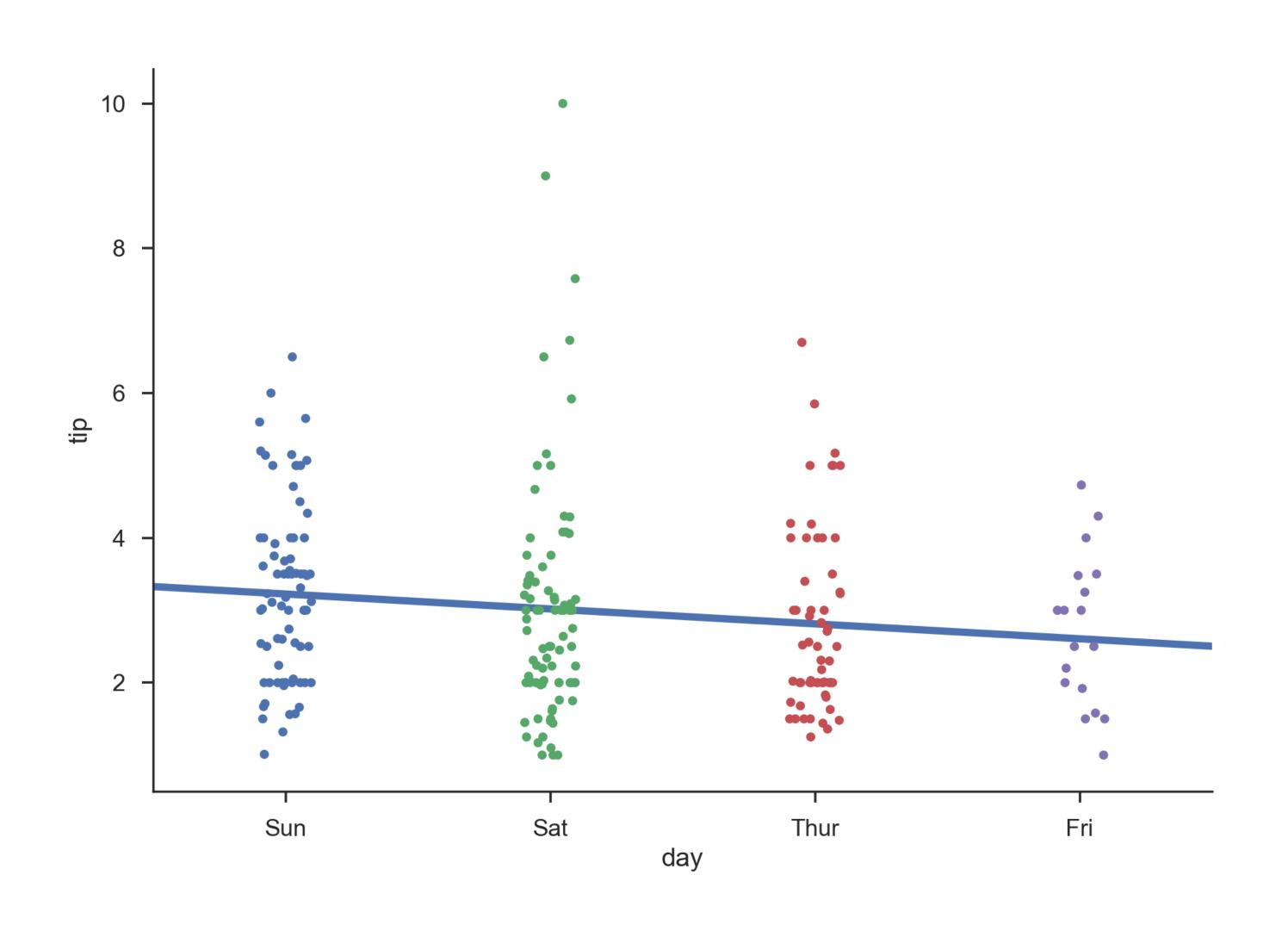


```
Factorized
                                   Raw
In [4]: codes, labels = pd.factorize(tips['day'])
 ...: codes
 • • • •
Out[4]:
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2])
```

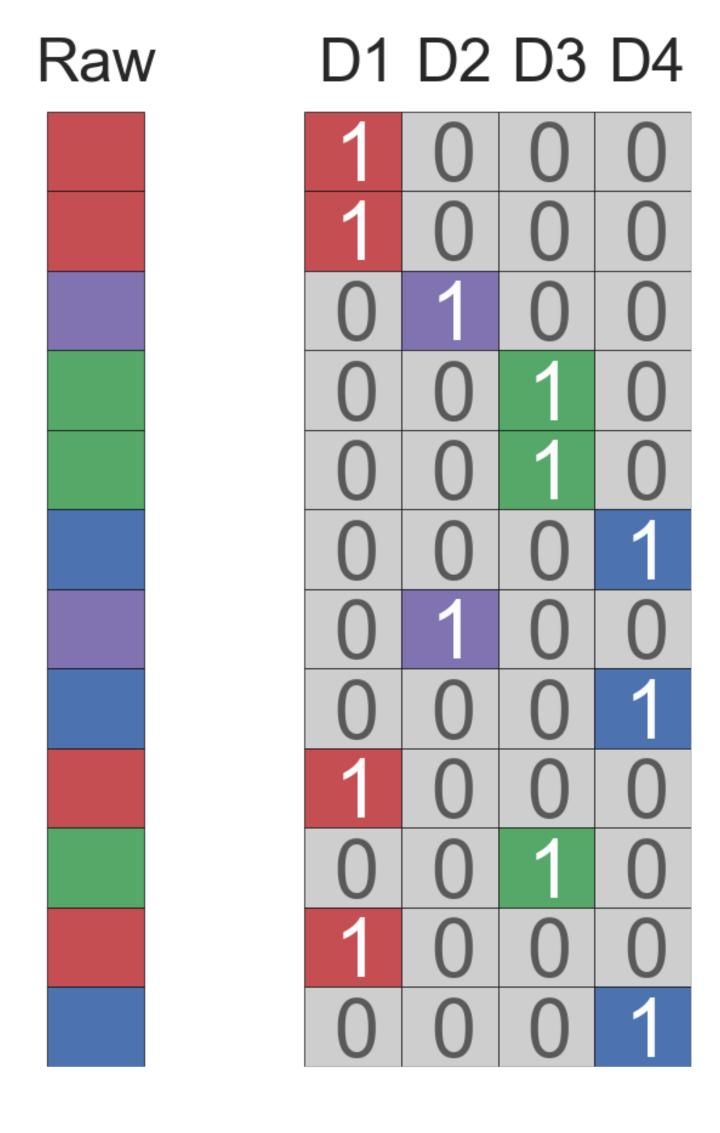
That "worked", but

- Ordering becomes important
- All categories are equally spaced
- All categories have equal effects*

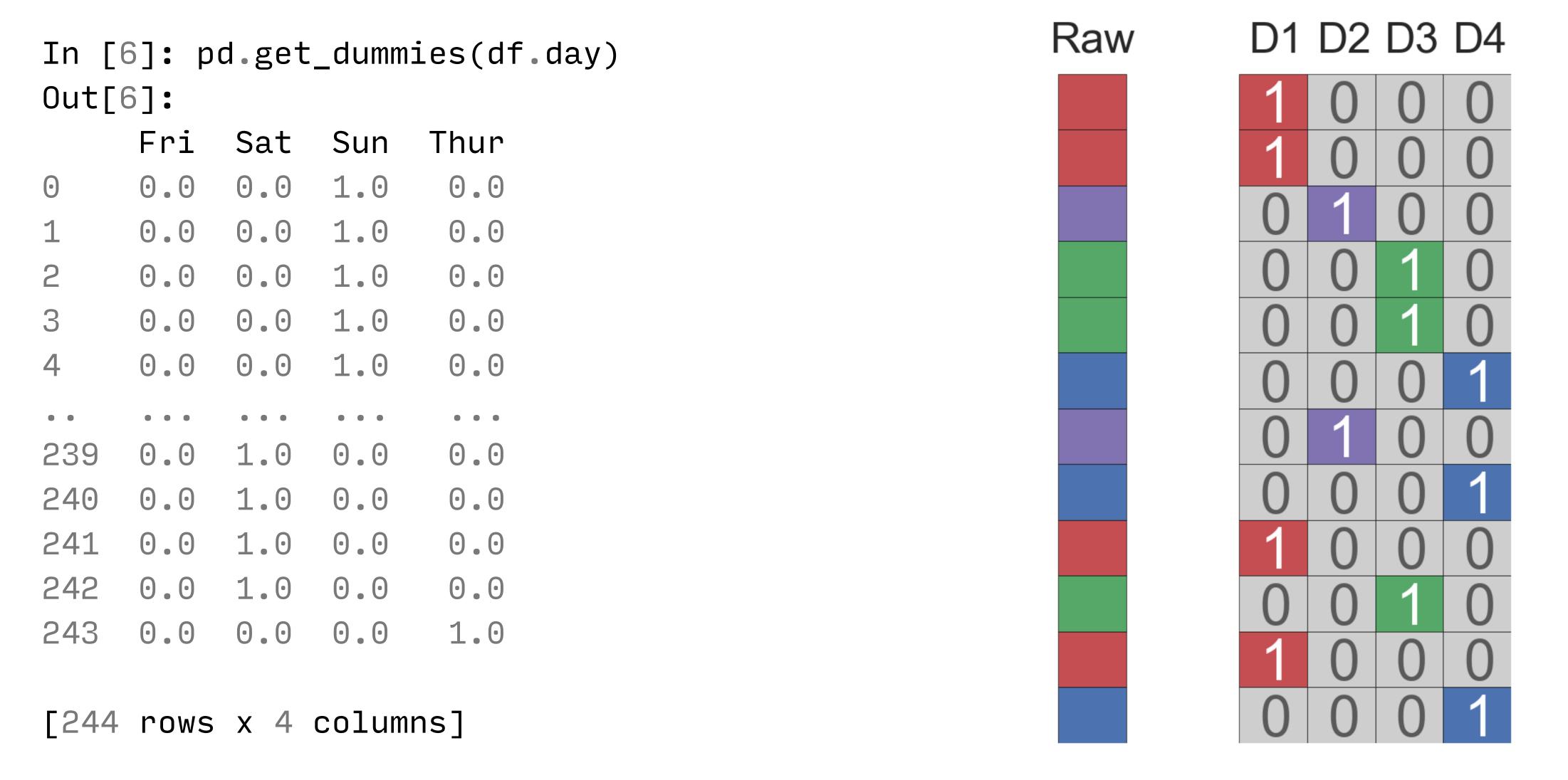
$$\frac{\Delta \text{tip}}{\Delta(\text{Sun.} \to \text{Sat.})} = \frac{\Delta \text{tip}}{\Delta(\text{Thur.} \to \text{Fri.})}$$



transformations: Dummy Encoding



transformations: Dummy Encoding



transformations: pd.get_dummies

```
In [7]: X_dummies = pd.get_dummies(X)
  ...: X_dummies.head()
Out[7]:
  total_bill size sex_Female sex_Male smoker_No
                                              smoker_Yes
                                                         day_Fri
       16.99
               2
                        1.0
                                 0.0
                                          1.0
                                                     0.0
                                                             0.0
      10.34
                        0.0
                                 1.0
                                          1.0
                                                     0.0
                                                            0.0
      21.01 3
                            1.0
                        0.0
                                          1.0
                                                     0.0
                                                            0.0
      23.68 2
                        0.0 1.0
                                          1.0
                                                     0.0 0.0
       24.59
                        1.0
                             \odot . \odot
                                          1.0
                                                     0.0
                                                           0.0
  day_Sat day_Sun day_Thur time_Dinner time_Lunch
      0.0
                      0.0
                                  1.0
              1.0
                                            0.0
0
      0.0
             1.0
                  0.0
                                  1.0
                                            0.0
             1.0
      0.0
                  0.0
                                  1.0
                                            0.0
              1.0
      0.0
                                  1.0
                  0.0
                                            0.0
              1.0
                   \Theta . \Theta
      0.0
                                  1.0
                                            0.0
```

transformations: pd.get_dummies

```
In [8]: from sklearn.linear_model import LinearRegression
   ...: lm = LinearRegression().fit(X_dummies, y)
   • • • •
   ...: yhat = lm.predict(X_dummies)
   ...: plt.scatter(y, y - yhat)
                                          Dummy-Encoded Regression
                         residual
```

The last solution is brittle

- 1. We can't easily go from dummies back to categoricals
- 2. Doesn't integrate with scikit-learn Pipeline objects.
- 3. If working with a larger dataset and partial_fit, codes could be missing from subsets of the data.
- 4. Memory inefficient if there are many records relative to distinct categories

```
Step 1: Categorize
In [9]: columns = ['sex', 'smoker', 'day', 'time']
   : tips[columns] = tips[columns].apply(lambda x: x.astype('category'))
   : tips.info()
In [9]: tips.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 7 columns):
total_bill 244 non-null float64
tip
             244 non-null float64
             244 non-null category
sex
smoker
             244 non-null category
             244 non-null category
day
time
             244 non-null category
             244 non-null int64
size
dtypes: category(4), float64(2), int64(1)
memory usage: 6.8 KB
```

Stores values information in the type

- Categories
- Order

Step 2: Transformer

```
import numpy as np
import pandas as pd
from sklearn.pipeline import TransformerMixin

class DummyEncoder(TransformerMixin):
...
```

class DummyEncoder(TransformerMixin):

```
def fit(self, X, y=None):
    self.index_ = X.index
    self.columns_ = X.columns
    self.cat_columns_ = X.select_dtypes(include=['category']).columns
    self.non_cat_columns_ = X.columns.drop(self.cat_columns_)
    self.cat_map_ = {col: X[col].cat for col in self.cat_columns_}
    left = len(self.non_cat_columns_)
    self.cat_blocks_ = {}
    for col in self.cat_columns_:
        right = left + len(X[col].cat.categories)
        self.cat_blocks_[col], left = slice(left, right), right
    return self
```

```
class DummyEncoder(TransformerMixin):
    ...

def transform(self, X, y=None):
    return np.asarray(pd.get_dummies(X))
```

```
class DummyEncoder(TransformerMixin):
    def inverse_transform(self, X):
        non_cat = pd.DataFrame(X[:, :len(self.non_cat_columns_)],
                               columns=self.non_cat_columns_)
        cats = []
        for col, cat in self.cat_map_.items():
            slice_ = self.cat_blocks_[col]
            codes = X[:, slice_].argmax(1)
            series = pd.Series(pd.Categorical.from_codes()
                codes, cat.categories, ordered=cat.ordered
            ), name=col)
            cats.append(series)
        df = pd.concat([non_cat] + cats, axis=1)[self.columns_]
        return df
```

```
In [14]: X = tips.drop('tip', axis=1)
    ...: y = tips['tip']
    • • • •
    ...: pipe = make_pipeline(
    DummyEncoder(),
    LinearRegression()
    . . . : )
    ...: pipe.fit(X, y)
Out[14]: Pipeline(
    steps=[('dummyencoder',
            <DummyEncoder object at 0x10992af60>),
           ('linearregression',
            LinearRegression(copy_X=True, fit_intercept=True,
                            n_jobs=1, normalize=False))])
```

Takeaway

Takeaway

- That particular transformer isn't the point
- Pandas is evolving further, more bridges needed
- Be comfortable writing the shims (or write a library to do it?)

Takeaway

https://mail.python.org/mailman/listinfo/pandas-dev

https://github.com/pydata/pandas



