Custom transformers + patsy & statsmodels

Lecture 14

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Custom sklearn transformers

FunctionTransformer

The simplest way to create a new transformer is to use `FunctionTransformer()` from the preprocessing submodule which allows for converting a Python function into a transformer.

```
from sklearn.preprocessing import FunctionTransformer
X = pd.DataFrame({"x1": range(1,6), "x2": range(5, 0, -1)})
```

```
log_transform = FunctionTransformer(np.log)
lt = log_transform.fit(X)
lt
```

```
FunctionTransformer(func=<ufunc 'log'>)
```

```
lt.transform(X)
```

```
       x1      x2
0  0.0000  1.6094
1  0.6931  1.3863
2  1.0986  1.0986
3  1.3863  0.6931
4  1.6094  0.0000
```

```
lt.get_params()
```

```
{'accept_sparse': False, 'check_inverse': True, 'feat
```

```
dir(lt)
```

```
['__annotate_func__', '__class__', '__delattr__', '__
```

```
lt.inverse_transform(lt.transform(X))
```

```
       x1      x2
0  0.0000  1.6094
1  0.6931  1.3863
2  1.0986  1.0986
3  1.3863  0.6931
4  1.6094  0.0000
```

Transformer w/ inverse

```
from sklearn.preprocessing import FunctionTransformer
X = pd.DataFrame({"x1": range(1,6), "x2": range(5, 0, -1)})

log_transform = FunctionTransformer(np.log, np.exp)
lt = log_transform.fit(X)
```

```
lt.transform(X)
```

```
       x1      x2
0  0.0000  1.6094
1  0.6931  1.3863
2  1.0986  1.0986
3  1.3863  0.6931
4  1.6094  0.0000
```

```
lt.inverse_transform(lt.transform(X))
```

```
    x1   x2
0  1.0  5.0
1  2.0  4.0
2  3.0  3.0
3  4.0  2.0
4  5.0  1.0
```

Input types

```python
def interact(X, y = None):
  return np.c_[X, X[:,0] * X[:,1]]
```

```python
X = pd.DataFrame({"x1": range(1,6),
                  "x2": range(5, 0, -1)})
FunctionTransformer(
  interact
).fit_transform(X)
```

```
pandas.errors.InvalidIndexError: (slice(None, No
```

```python
Z = np.array(X)

FunctionTransformer(
  interact
).fit_transform(Z)
```

```
array([[1, 5, 5],
       [2, 4, 8],
       [3, 3, 9],
       [4, 2, 8],
       [5, 1, 5]])
```

```python
FunctionTransformer(
  interact, validate=True
).fit_transform(X)
```

```
array([[1, 5, 5],
       [2, 4, 8],
       [3, 3, 9],
       [4, 2, 8],
       [5, 1, 5]])
```

```python
FunctionTransformer(
  interact, validate=True
).fit_transform(Z)
```

```
array([[1, 5, 5],
       [2, 4, 8],
       [3, 3, 9],
       [4, 2, 8],
       [5, 1, 5]])
```

The `validate` argument both checks that `X` is 2d as well as converts it to a np.array.

Build your own transformer

For a more full featured transformer, we construct it as a class that inherits from the `BaseEstimator` and `TransformerMixin` classes from the `base` submodule.

```python
from sklearn.base import BaseEstimator, TransformerMixin

class scaler(TransformerMixin, BaseEstimator):
  def __init__(self, m = 1, b = 0):
    self.m = m
    self.b = b

  def fit(self, X, y=None):
    return self

  def transform(self, X, y=None):
    return X*self.m + self.b
```

```python
X = pd.DataFrame({
  "x1": range(1,6),
  "x2": range(5, 0, -1)}
); X
```

```
   x1  x2
0   1   5
1   2   4
2   3   3
3   4   2
4   5   1
```

```python
double = scaler(2)
double.get_params()
```

```
{'b': 0, 'm': 2}
```

```python
double.fit_transform(X)
```

```
   x1  x2
0   2  10
1   4   8
2   6   6
3   8   4
4  10   2
```

```python
double.set_params(b=-3).fit_transform(X)
```

```
   x1  x2
0  -1   7
1   1   5
2   3   3
3   5   1
4   7  -1
```

What else do we get?

```
print(
  np.array(dir(double))
)
```

```
['__class__' '__delattr__' '__dict__' '__dir__' '__doc__' '__eq__'
 '__firstlineno__' '__format__' '__ge__' '__getattribute__' '__getstate__'
 '__gt__' '__hash__' '__init__' '__init_subclass__' '__le__' '__lt__'
 '__module__' '__ne__' '__new__' '__reduce__' '__reduce_ex__' '__repr__'
 '__setattr__' '__setstate__' '__sizeof__' '__sklearn_clone__'
 '__sklearn_tags__' '__static_attributes__' '__str__' '__subclasshook__'
 '__weakref__' '_doc_link_module' '_doc_link_template'
 '_doc_link_url_param_generator' '_get_class_level_metadata_request_values'
 '_get_doc_link' '_get_metadata_request' '_get_param_names' '_get_params_html'
 '_html_repr' '_repr_html_inner' '_repr_mimebundle_'
 '_sklearn_auto_wrap_output_keys' '_validate_params' 'b' 'fit' 'fit_transform'
 'get_metadata_routing' 'get_params' 'm' 'set_params' 'transform']
```

Demo - Interaction Transformer

Useful methods

We employed a couple of special methods that are worth mentioning in a little more detail.

- `validate_data()` is responsible for setting and checking the `n_features_in_` and the `feature_names_in_` attributes respectively.
- In general, it is run during `fit()` with `reset=True` in which case the respective attribute will be set.
- Later, in `transform()` it is called again with `reset=False` and the properties of `X` will be checked against the values in the attribute.
- Worth using as it promotes a consistent interface with sklearn and also provide convenient error checking

`check_is_fitted()`

This is another useful helper function from `sklearn.utils` - it is fairly simplistic in that it checks for the existence of a specified attribute. If no attribute is given then it checks for any attributes ending in `_` that do not begin with `__`.

Again this is useful for providing a consistent interface and useful error / warning messages.

See also the other `check*()` functions in `sklearn.utils`.

`check_estimator()`

Once you have built a custom estimator, `check_estimator()` from `sklearn.utils.estimator_checks` can be used to verify that it fully complies with the sklearn API.

```python
from sklearn.utils.estimator_checks import check_estimator

check_estimator(scaler())
```

```
AssertionError: `scaler.fit()` does not set the `n_features_in_` attribute. You might
```

It runs a large battery of standardized tests (input validation, clone/set-params round-trips, fit/transform contract, etc.) and raises on any failure — making it the canonical way to catch interface issues before using a custom estimator in a pipeline.

`parametrize_with_checks()` is a pytest-friendly variant that yields individual test cases, useful when you want failures

Other custom estimators

If you want to implement your own custom modeling function it is possible, there are different Mixin base classes in `sklearn.base` that provide the common core interface.

Class	Description
`base.BiclusterMixin`	Mixin class for all bicluster estimators
`base.ClassifierMixin`	Mixin class for all classifiers
`base.ClusterMixin`	Mixin class for all cluster estimators
`base.DensityMixin`	Mixin class for all density estimators
`base.RegressorMixin`	Mixin class for all regression estimators
`base.TransformerMixin`	Mixin class for all transformers
`base.OneToOneFeatureMixin`	Provides get_feature_names_out for simple transformers

patsy

patsy

> `patsy` is a Python package for describing statistical models (especially linear models, or models that have a linear component) and building design matrices. It is closely inspired by and compatible with the formula mini-language used in R and S.
>
> …
>
> Patsy's goal is to become the standard high-level interface to describing statistical models in Python, regardless of what particular model or library is being used underneath.

Formulas

```python
from patsy import ModelDesc
```

```python
ModelDesc.from_formula("y ~ a + a:b + np.log(x)")
```

```
ModelDesc(lhs_termlist=[Term([EvalFactor('y')])],
          rhs_termlist=[Term([]),
                        Term([EvalFactor('a')]),
                        Term([EvalFactor('a'), EvalFactor('b')]),
                        Term([EvalFactor('np.log(x)')])])
```

```python
ModelDesc.from_formula("y ~ a*b + np.log(x) - 1")
```

```
ModelDesc(lhs_termlist=[Term([EvalFactor('y')])],
          rhs_termlist=[Term([EvalFactor('a')]),
                        Term([EvalFactor('b')]),
                        Term([EvalFactor('a'), EvalFactor('b')]),
                        Term([EvalFactor('np.log(x)')])])
```

This general syntax is known as Wilkinson Notation and comes from Wilkinson and Rogers. "Symbolic description of

Model matrix

```python
from patsy import demo_data, dmatrix, dmatrices
```

```python
data = demo_data(
  "y", "a", "b", "x1", "x2"
)
pd.DataFrame(data)
```

```
    a   b      x1      x2       y
0  a1  b1  1.7641 -0.1032  1.4941
1  a1  b2  0.4002  0.4106 -0.2052
2  a2  b1  0.9787  0.1440  0.3131
3  a2  b2  2.2409  1.4543 -0.8541
4  a1  b1  1.8676  0.7610 -2.5530
5  a1  b2 -0.9773  0.1217  0.6536
6  a2  b1  0.9501  0.4439  0.8644
7  a2  b2 -0.1514  0.3337 -0.7422
```

```python
dmatrix("a + a:b + np.exp(x1)", data)
```

```
DesignMatrix with shape (8, 5)
  Intercept  a[T.a2]  a[a1]:b[T.b2]  a[a2]:b[T.b2]  np.exp(x1)
          1        0              0              0     5.83604
          1        0              1              0     1.49206
          1        1              0              0     2.66110
          1        1              0              1     9.40173
          1        0              0              0     6.47247
          1        0              1              0     0.37633
          1        1              0              0     2.58594
          1        1              0              1     0.85954
  Terms:
    'Intercept' (column 0)
    'a' (column 1)
    'a:b' (columns 2:4)
    'np.exp(x1)' (column 4)
```

Model matrices

```
y, X  = dmatrices("y ~ a + a:b + np.exp(x1)", data)
```

```
y
```

```
DesignMatrix with shape (8, 1)
         y
   1.49408
  -0.20516
   0.31307
  -0.85410
  -2.55299
   0.65362
   0.86444
  -0.74217
  Terms:
    'y' (column 0)
```

```
X
```

```
DesignMatrix with shape (8, 5)
  Intercept  a[T.a2]  a[a1]:b[T.b2]  a[a2]:b[T.b2]  np.exp(x1)
          1        0              0              0     5.83604
          1        0              1              0     1.49206
          1        1              0              0     2.66110
          1        1              0              1     9.40173
          1        0              0              0     6.47247
          1        0              1              0     0.37633
          1        1              0              0     2.58594
          1        1              0              1     0.85954
  Terms:
    'Intercept' (column 0)
    'a' (column 1)
    'a:b' (columns 2:4)
    'np.exp(x1)' (column 4)
```

as DataFrames

```
dmatrix("a + a:b + np.exp(x1)", data, return_type='dataframe')
```

```
   Intercept  a[T.a2]  a[a1]:b[T.b2]  a[a2]:b[T.b2]  np.exp(x1)
0        1.0      0.0            0.0            0.0      5.8360
1        1.0      0.0            1.0            0.0      1.4921
2        1.0      1.0            0.0            0.0      2.6611
3        1.0      1.0            0.0            1.0      9.4017
4        1.0      0.0            0.0            0.0      6.4725
5        1.0      0.0            1.0            0.0      0.3763
6        1.0      1.0            0.0            0.0      2.5859
7        1.0      1.0            0.0            1.0      0.8595
```

Formula Syntax

Code	Description	Example
`+`	unions terms on the left and right	`a+a` ⇒ `a`
`-`	removes terms on the right from terms on the left	`a+b-a` ⇒ `b`
`:`	constructs interactions between each term on the left and right	`(a+b):c` ⇒ `a:c + b:c`
`*`	short-hand for terms and their interactions	`a*b` ⇒ `a + b + a:b`
`/`	short-hand for left terms and their interactions with right terms	`a/b` ⇒ `a + a:b`
`I()`	used for arithmetic calculations	`I(x1 + x2)`
`Q()`	used to quote column names, e.g. columns with spaces or symbols	`Q('bad name!')`
`C()`	used for categorical data coding	`C(a, Treatment('a2'))`

Examples

```
dmatrix("x:y", demo_data("x","y","z"))
```

```
DesignMatrix with shape (5, 2)
  Intercept      x:y
          1 -1.72397
          1  0.38018
          1 -0.14814
          1 -0.23130
          1  0.76682
  Terms:
    'Intercept' (column 0)
    'x:y' (column 1)
```

```
dmatrix("x*y", demo_data("x","y","z"))
```

```
DesignMatrix with shape (5, 4)
  Intercept        x        y      x:y
          1  1.76405 -0.97728 -1.72397
          1  0.40016  0.95009  0.38018
          1  0.97874 -0.15136 -0.14814
          1  2.24089 -0.10322 -0.23130
          1  1.86756  0.41060  0.76682
  Terms:
    'Intercept' (column 0)
    'x' (column 1)
    'y' (column 2)
    'x:y' (column 3)
```

```
dmatrix("x/y", demo_data("x","y","z"))
```

```
DesignMatrix with shape (5, 3)
  Intercept        x      x:y
          1  1.76405 -1.72397
          1  0.40016  0.38018
          1  0.97874 -0.14814
          1  2.24089 -0.23130
          1  1.86756  0.76682
  Terms:
    'Intercept' (column 0)
    'x' (column 1)
    'x:y' (column 2)
```

```
dmatrix("x*(y+z)", demo_data("x","y","z"))
```

```
DesignMatrix with shape (5, 6)
  Intercept        x         y        z       x:y      x:z
          1  1.76405  -0.97728  0.14404  -1.72397  0.25410
          1  0.40016   0.95009  1.45427   0.38018  0.58194
          1  0.97874  -0.15136  0.76104  -0.14814  0.74486
          1  2.24089  -0.10322  0.12168  -0.23130  0.27266
          1  1.86756   0.41060  0.44386   0.76682  0.82894
  Terms:
    'Intercept' (column 0)
    'x' (column 1)
    'y' (column 2)
    'z' (column 3)
    'x:y' (column 4)
    'x:z' (column 5)
```

Intercept Examples (-1)

```
dmatrix("x", demo_data("x","y","z"))
```

```
DesignMatrix with shape (5, 2)
  Intercept        x
          1  1.76405
          1  0.40016
          1  0.97874
          1  2.24089
          1  1.86756
  Terms:
    'Intercept' (column 0)
    'x' (column 1)
```

```
dmatrix("x-1", demo_data("x","y","z"))
```

```
DesignMatrix with shape (5, 1)
        x
  1.76405
  0.40016
  0.97874
  2.24089
  1.86756
  Terms:
    'x' (column 0)
```

```
dmatrix("-1 + x", demo_data("x","y","z"))
```

```
DesignMatrix with shape (5, 1)
        x
  1.76405
  0.40016
  0.97874
  2.24089
  1.86756
  Terms:
    'x' (column 0)
```

Intercept Examples (0)

```python
dmatrix("x+0", demo_data("x","y","z"))
```

```
DesignMatrix with shape (5, 1)
        x
  1.76405
  0.40016
  0.97874
  2.24089
  1.86756
  Terms:
    'x' (column 0)
```

```python
dmatrix("x-0", demo_data("x","y","z"))
```

```
DesignMatrix with shape (5, 2)
  Intercept        x
          1  1.76405
          1  0.40016
          1  0.97874
          1  2.24089
          1  1.86756
  Terms:
    'Intercept' (column 0)
    'x' (column 1)
```

```python
dmatrix("x - (-0)", demo_data("x","y","z"))
```

```
DesignMatrix with shape (5, 1)
        x
  1.76405
  0.40016
  0.97874
  2.24089
  1.86756
  Terms:
    'x' (column 0)
```

Design Info

One of the key features of the design matrix object is that it retains all the necessary details (including stateful transforms) that are necessary to apply to new data inputs (e.g. for prediction).

```python
d = dmatrix("a + a:b + np.exp(x1)", data, return_type='dataframe')
d.design_info
```

```
DesignInfo(['Intercept',
            'a[T.a2]',
            'a[a1]:b[T.b2]',
            'a[a2]:b[T.b2]',
            'np.exp(x1)'],
           factor_infos={EvalFactor('a'): FactorInfo(factor=EvalFactor('a'),
                                    type='categorical',
                                    state=<factor state>,
                                    categories=('a1', 'a2')),
                         EvalFactor('b'): FactorInfo(factor=EvalFactor('b'),
                                    type='categorical',
                                    state=<factor state>,
                                    categories=('b1', 'b2')),
                         EvalFactor('np.exp(x1)'): FactorInfo(factor=EvalFactor('np.exp(x1)'),
                                    type='numerical',
                                    state=<factor state>,
                                    num_columns=1)},
           term_codings=OrderedDict([(Term([]),
                                      [SubtermInfo(factors=(),
                                                   contrast_matrices={},
                                                   num_columns=1)]),
                                     (Term([EvalFactor('a')]),
```

```
[SubtermInfo(factors=(EvalFactor('a'),),
             contrast_matrices={EvalFactor('a'): ContrastMatrix(array
```

Stateful transforms

```python
data = {"x1": np.random.normal(size=10)}
new_data = {"x1": np.random.normal(size=10)}
```

```python
d = dmatrix("scale(x1)", data)
d
```

```
DesignMatrix with shape (10, 2)
  Intercept  scale(x1)
          1   -1.30275
          1    1.15973
          1   -0.06413
          1    0.00408
          1    0.60267
          1    0.24535
          1   -1.01277
          1    1.98161
          1   -0.43564
          1   -1.17816
  Terms:
    'Intercept' (column 0)
    'scale(x1)' (column 1)
```

```python
np.mean(d, axis=0)
```

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

```python
pred = dmatrix(d.design_info, new_data)
pred
```

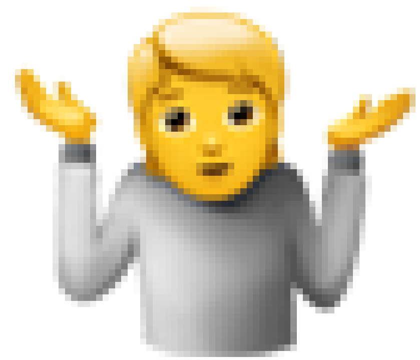
```
DesignMatrix with shape (10, 2)
  Intercept  scale(x1)
          1   -1.27050
          1    0.93536
          1   -0.98273
          1   -0.26053
          1    0.20715
          1   -1.07425
          1   -1.44949
          1   -0.46439
          1   -0.63943
          1    0.50280
  Terms:
    'Intercept' (column 0)
    'scale(x1)' (column 1)
```

```python
np.mean(pred, axis=0)
```

```
array([ 1.    , -0.4496])
```

scikit-learn + Patsy

The state of affairs here is a bit of a mess at the moment - previously the `sklego` package implemented a `PatsyTransformer` class that has since been deprecated in favor of the `FormulaicTransformer` which uses the `formulaic` package for formula handling.



A PatsyTransformer

```python
from patsy import dmatrix, build_design_matrices
from sklearn.utils.validation import check_is_fitted
from sklearn.base import BaseEstimator, TransformerMixin

class PatsyTransformer(BaseEstimator, TransformerMixin):
    def __init__(self, formula):
        self.formula = formula

    def fit(self, X, y=None):
        m = dmatrix(self.formula, X)
        assert np.array(m).shape[0] == np.array(X).shape[0]
        self.design_info_ = m.design_info
        return self

    def transform(self, X):
        check_is_fitted(self, 'design_info_')
        return build_design_matrices([self.design_info_], X)[0]
```

```
df = pd.DataFrame({
  "y": [2, 2, 4, 4, 6], "x": [1, 2, 3, 4, 5],
  "a": ["yes", "yes", "no", "no", "yes"]
})
X, y = df[["x", "a"]], df[["y"]].values
```

```
pt = PatsyTransformer("x*a + np.log(x)")
pt.fit_transform(X)
```

```
DesignMatrix with shape (5, 5)
  Intercept  a[T.yes]  x  x:a[T.yes]  np.log(x)
          1         1  1           1    0.00000
          1         1  2           2    0.69315
          1         0  3           0    1.09861
          1         0  4           0    1.38629
          1         1  5           5    1.60944
  Terms:
    'Intercept' (column 0)
    'a' (column 1)
    'x' (column 2)
    'x:a' (column 3)
    'np.log(x)' (column 4)
```

```
make_pipeline(
  PatsyTransformer("x*a + np.log(x)"),
  StandardScaler()
).fit_transform(X)
```

```
array([[ 0.    ,  0.8165, -1.4142, -0.3235, -1.6845],
       [ 0.    ,  0.8165, -0.7071,  0.2157, -0.4651],
       [ 0.    , -1.2247,  0.    , -0.8627,  0.2483],
       [ 0.    , -1.2247,  0.7071, -0.8627,  0.7544],
       [ 0.    ,  0.8165,  1.4142,  1.8332,  1.1469]])
```

statsmodels

statsmodels

> statsmodels is a Python module that provides classes and functions for the estimation of many different statistical models, as well as for conducting statistical tests, and statistical data exploration. An extensive list of result statistics are available for each estimator. The results are tested against existing statistical packages to ensure that they are correct.

```python
import statsmodels.api as sm
import statsmodels.formula.api as smf
import statsmodels.tsa.api as tsa
```

`statsmodels` uses slightly different terminology for referring to `y` (dependent / response) and `x` (independent / explanatory) variables.

Specifically it uses `endog` and `exog` to refer to `y` and `x` variable(s) respectively.

This is particularly important when using the main API, less so when using the formula API.

OpenIntro Loans data

> This data set represents thousands of loans made through the Lending Club platform, which is a platform that allows individuals to lend to other individuals. Of course, not all loans are created equal. Someone who is a essentially a sure bet to pay back a loan will have an easier time getting a loan with a low interest rate than someone who appears to be riskier. And for people who are very risky? They may not even get a loan offer, or they may not have accepted the loan offer due to a high interest rate. It is important to keep that last part in mind, since this data set only represents loans actually made, i.e. do not mistake this data for loan applications!

For the full data dictionary see here. We have removed some of the columns to make the data set more reasonably sized and also dropped any rows with missing values.

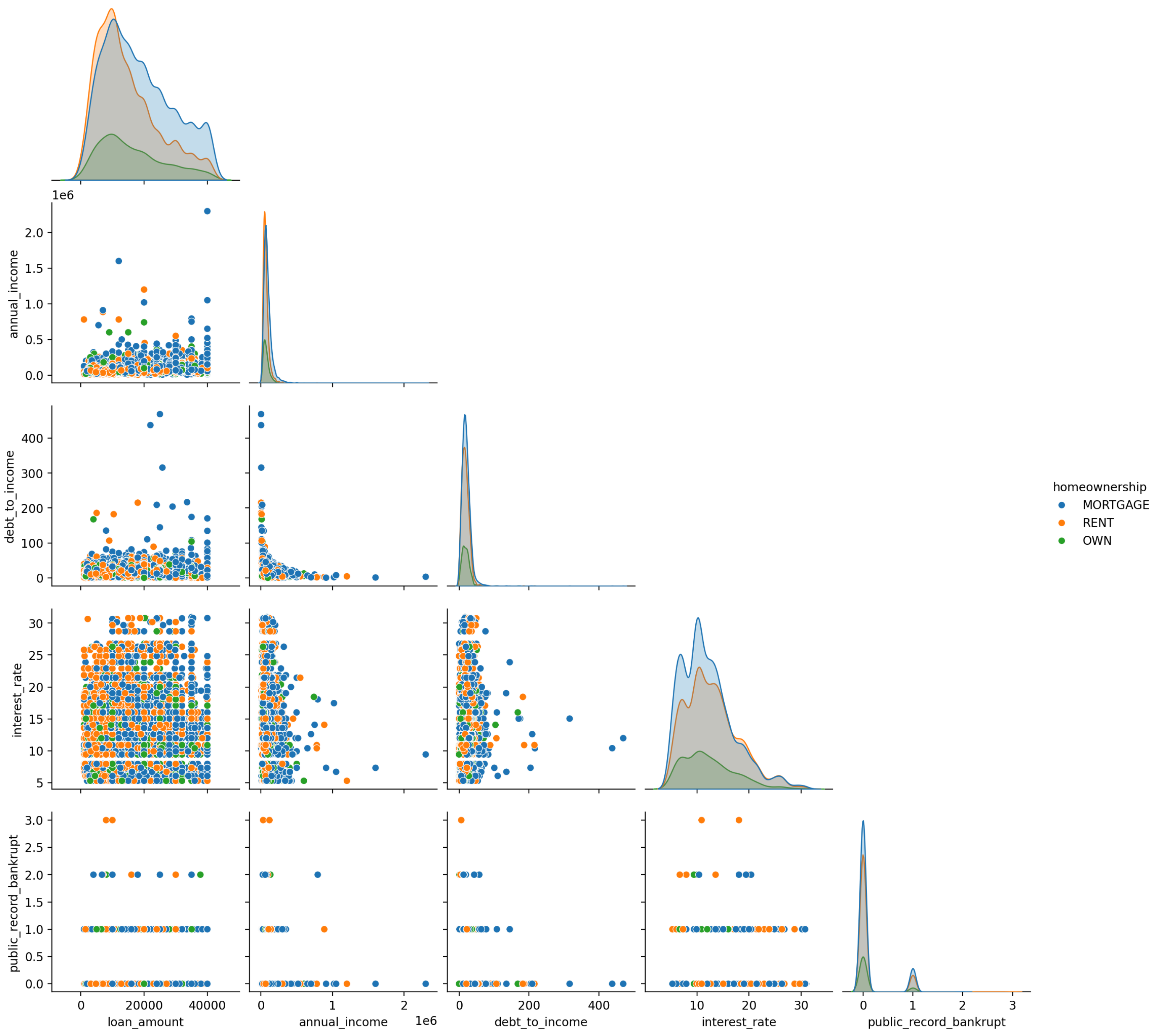
```
loans = pd.read_csv("data/openintro_loans.csv")
loans
```

```
     state  emp_length  term homeownership  annual_income  ... loan_amount  grade  interest_rate
0       NJ           3    60      MORTGAGE        90000.0  ...       28000      C          14.07
1       HI          10    36          RENT        40000.0  ...        5000      C          12.61
2       WI           3    36          RENT        40000.0  ...        2000      D          17.09
3       PA           1    36          RENT        30000.0  ...       21600      A           6.72
4       CA          10    36          RENT        35000.0  ...       23000      C          14.07
...    ...         ...   ...           ...            ...  ...         ...    ...            ...
9177    TX          10    36          RENT       108000.0  ...       24000      A           7.35
9178    PA           8    36      MORTGAGE       121000.0  ...       10000      D          19.03
9179    CT          10    36      MORTGAGE        67000.0  ...       30000      E          23.88
9180    WI           1    36      MORTGAGE        80000.0  ...       24000      A           5.32
9181    CT           3    36          RENT        66000.0  ...       12800      B          10.91
```

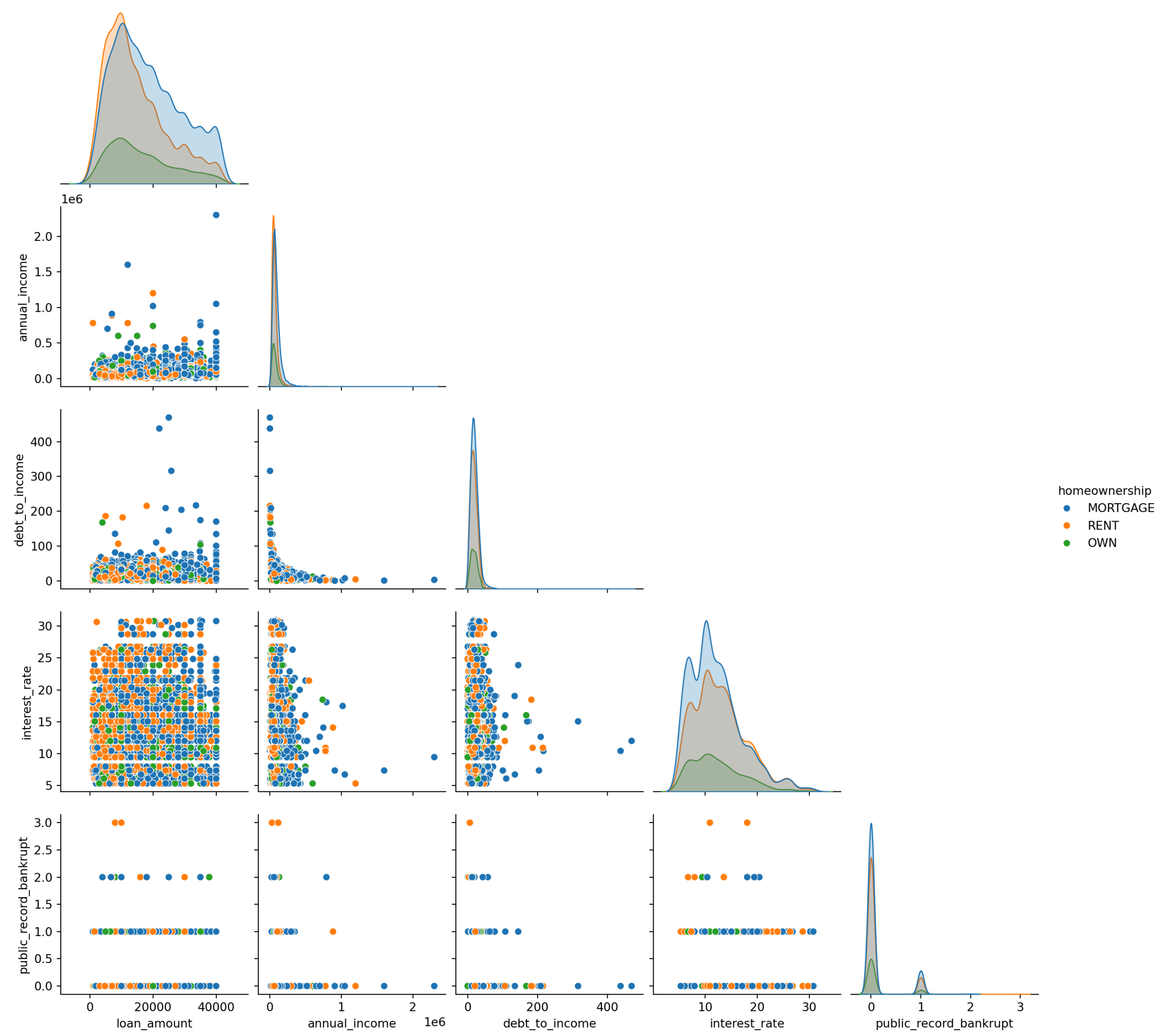
```
      public_record_bankrupt  loan_status
0                          0      Current
1                          1      Current
2                          0      Current
3                          0      Current
4                          0      Current
...                      ...          ...
9177                       1      Current
9178                       0      Current
```

```
1 print(loans.columns)
```

```
Index(['state', 'emp_length', 'term', 'homeownership', 'annual_income', 'verified_income',
       'debt_to_income', 'total_credit_limit', 'total_credit_utilized', 'num_cc_carrying_balance',
       'loan_purpose', 'loan_amount', 'grade', 'interest_rate', 'public_record_bankrupt',
       'loan_status'],
      dtype='str')
```



homeownership
MORTGAGE
RENT
OWN
annual_income
debt_to_income
interest_rate
public_record_bankrupt
loan_amount
1e6



1e6
annual_income
debt_to_income
interest_rate
public_record_bankrupt
loan_amount
annual_income
1e6
debt_to_income
interest_rate
public_record_bankrupt
homeownership
MORTGAGE
RENT
OWN

OLS

```
y = loans["loan_amount"]
X = loans[["homeownership", "annual_income", "debt_to_income", "interest_rate", "public_recor

model = sm.OLS(endog=y, exog=X)
```

```
ValueError: Pandas data cast to numpy dtype of object. Check input data with np.asarray(data).
```

What do you think the issue is here?

The error occurs because `X` contains mixed types - specifically we have categorical data columns which cannot be directly converted to a numeric dtype so we need to take care of the dummy coding for statsmodels (with this interface).

```
X_dc = pd.get_dummies(X)
model = sm.OLS(endog=y, exog=X_dc)
```

```
ValueError: Pandas data cast to numpy dtype of object. Check input data with np.asarray(data).
```

```
X_dc.dtypes
```

```
annual_income               float64
debt_to_income              float64
interest_rate               float64
public_record_bankrupt        int64
homeownership_MORTGAGE         bool
homeownership_OWN              bool
homeownership_RENT             bool
dtype: object
```

```
X_dc = pd.get_dummies(X, dtype='int')
model = sm.OLS(endog=y, exog=X_dc)
```

```python
model
```

```
<statsmodels.regression.linear_model.OLS object at 0x35b3f9f90>
```

```python
np.array(dir(model))
```

```
array(['__class__', '__delattr__', '__dict__', '__dir__', '__doc__', '__eq__',
       '__firstlineno__', '__format__', '__ge__', '__getattribute__',
       '__getstate__', '__gt__', '__hash__', '__init__', '__init_subclass__',
       '__le__', '__lt__', '__module__', '__ne__', '__new__', '__reduce__',
       '__reduce_ex__', '__repr__', '__setattr__', '__sizeof__',
       '__static_attributes__', '__str__', '__subclasshook__', '__weakref__',
       '_check_kwargs', '_data_attr', '_df_model', '_df_resid',
       '_fit_collinear', '_fit_ridge', '_fit_zeros', '_formula_max_endog',
       '_get_init_kwds', '_handle_data', '_init_keys', '_kwargs_allowed',
       '_setup_score_hess', '_sqrt_lasso', 'data', 'df_model', 'df_resid',
       'endog', 'endog_names', 'exog', 'exog_names', 'fit', 'fit_regularized',
       'from_formula', 'get_distribution', 'hessian', 'hessian_factor',
       'information', 'initialize', 'k_constant', 'loglike', 'nobs',
       'pinv_wexog', 'predict', 'rank', 'score', 'weights', 'wendog', 'wexog',
       'whiten'], dtype='<U21')
```

Fitting and summary

```python
res = model.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            loan_amount   R-squared:                       0.135
Model:                            OLS   Adj. R-squared:                  0.135
Method:                 Least Squares   F-statistic:                     239.5
Date:                Tue, 24 Feb 2026   Prob (F-statistic):          2.33e-285
Time:                        09:25:42   Log-Likelihood:                -97245.
No. Observations:                9182   AIC:                         1.945e+05
Df Residuals:                    9175   BIC:                         1.946e+05
Df Model:                           6
Covariance Type:            nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
annual_income              0.0505      0.002     31.952      0.000       0.047       0.054
debt_to_income            65.6641      7.310      8.982      0.000      51.334      79.994
interest_rate            204.2480     20.448      9.989      0.000     164.166     244.330
public_record_bankrupt -1362.3253    306.019     -4.452      0.000   -1962.191    -762.460
homeownership_MORTGAGE  1.002e+04    357.245     28.048      0.000    9319.724    1.07e+04
homeownership_OWN       8880.4144    422.296     21.029      0.000    8052.620    9708.209
homeownership_RENT      7446.5385    351.641     21.177      0.000    6757.243    8135.834
==============================================================================
```

Formula interface

Most of the modeling interfaces are also provided by `smf` (`statsmodels.formula.api`), in which case `patsy` is used to construct the model matrices.

```
model = smf.ols(
  "loan_amount ~ homeownership + annual_income + debt_to_income + interest_rate + public_record_bankrupt",
  data = loans
)
res = model.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            loan_amount   R-squared:                       0.135
Model:                            OLS   Adj. R-squared:                  0.135
Method:                 Least Squares   F-statistic:                     239.5
Date:                Tue, 24 Feb 2026   Prob (F-statistic):          2.33e-285
Time:                        09:25:42   Log-Likelihood:                -97245.
No. Observations:                9182   AIC:                         1.945e+05
Df Residuals:                    9175   BIC:                         1.946e+05
Df Model:                           6
Covariance Type:            nonrobust
============================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------
Intercept                1.002e+04    357.245     28.048      0.000    9319.724    1.07e+04
homeownership[T.OWN]    -1139.5893    322.361     -3.535      0.000   -1771.489    -507.690
homeownership[T.RENT]   -2573.4652    221.101    -11.639      0.000   -3006.873   -2140.057
annual_income               0.0505      0.002     31.952      0.000       0.047       0.054
debt_to_income             65.6641      7.310      8.982      0.000      51.334      79.994
interest_rate             204.2480     20.448      9.989      0.000     164.166     244.330
public_record_bankrupt -1362.3253    306.019     -4.452      0.000   -1962.191    -762.460
==============================================================================
Omnibus:                      481.833   Durbin-Watson:                   2.002
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              916.542
Skew:                           0.391   Prob(JB):                    9.45e-200
Kurtosis:                       4.336   Cond. No.                     4.16e+05
```

```
================================================================================

Notes:
```

Result values and model parameters

```
1  res.params
```

```
Intercept                  10020.0036
homeownership[T.OWN]       -1139.5893
homeownership[T.RENT]      -2573.4652
annual_income                  0.0505
debt_to_income                65.6641
interest_rate                204.2480
public_record_bankrupt     -1362.3253
dtype: float64
```

```
1  res.bse
```

```
Intercept                  357.2449
homeownership[T.OWN]       322.3612
homeownership[T.RENT]      221.1013
annual_income                0.0016
debt_to_income               7.3104
interest_rate               20.4476
public_record_bankrupt     306.0191
dtype: float64
```

```
1  res.rsquared
```

```
np.float64(0.13542611095847423)
```

```
1  res.aic
```

```
np.float64(194503.99751598848)
```

```
1  res.bic
```

```
np.float64(194553.87251826216)
```

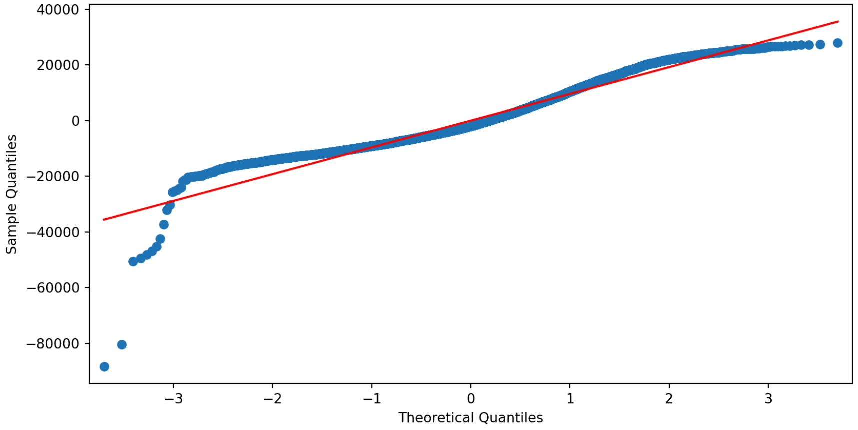
```
1  res.predict()
```

```
array([18621.862 , 11010.9402, 14346.1452, 11001
       19087.6239, 18474.006 , 11573.9102, 16203
       16631.5174, 19462.6034, 18283.8749, 26719
       15327.044 , 19588.3343, 14350.4342, 16320
       12285.762 , 13873.1568, 19674.8597, 25956
       ..., 19576.1693, 18304.6797, 15552.0573,
       18643.311 , 17631.7093, 21224.3819, 15264
       17676.6097, 17161.9604, 18764.4883, 19252
       16180.9411, 13397.0625, 15582.8136, 15698
       14183.3436, 12385.5385, 14503.0065, 22144
       14375.3617], shape=(9182,))
```

Diagnostic plots

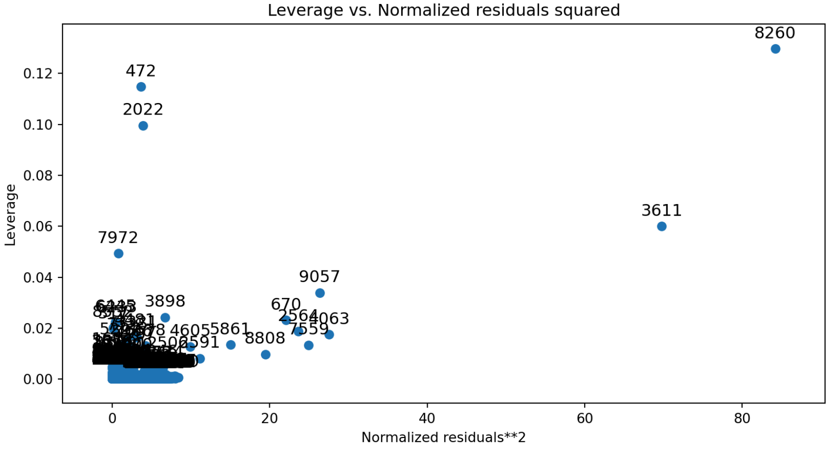
QQ Plot

```
plt.figure()
sm.graphics.qqplot(res.resid, line="s")
plt.show()
```



Leverage plot

```
plt.figure()
sm.graphics.plot_leverage_resid2(res)
plt.show()
```



Bushtail Possums

> Data representing possums in Australia and New Guinea. This is a copy of the data set by the same name in the DAAG package, however, the data set included here includes fewer variables.

```
possum = pd.read_csv("data/possum.csv")
possum
```

```
     site    pop sex  age  head_l  skull_w  total_l  tail_l
0       1    Vic   m  8.0    94.1     60.4     89.0    36.0
1       1    Vic   f  6.0    92.5     57.6     91.5    36.5
2       1    Vic   f  6.0    94.0     60.0     95.5    39.0
3       1    Vic   f  6.0    93.2     57.1     92.0    38.0
4       1    Vic   f  2.0    91.5     56.3     85.5    36.0
..    ...    ...  ..  ...     ...      ...      ...     ...
99      7  other   m  1.0    89.5     56.0     81.5    36.5
100     7  other   m  1.0    88.6     54.7     82.5    39.0
101     7  other   f  6.0    92.4     55.0     89.0    38.0
102     7  other   m  4.0    91.5     55.2     82.5    36.5
103     7  other   f  3.0    93.6     59.9     89.0    40.0

[104 rows x 8 columns]
```

Logistic regression models (GLM)

```
y = pd.get_dummies( possum["pop"], drop_first = True, dtype="int")
X = pd.get_dummies( possum.drop(["site","pop"], axis=1), dtype="int")

model = sm.GLM(y, X, family = sm.families.Binomial())
```

```
statsmodels.tools.sm_exceptions.MissingDataError: exog contains inf or nans
```

What went wrong this time?

Missing values

Missing values can be handled via `missing` argument, possible values are `"none"`, `"drop"`, and `"raise"`.

```
model = sm.GLM(y, X, family = sm.families.Binomial(), missing="drop")
res = model.fit()
print(res.summary())
```

Success vs failure

Note `endog` can be 1d or 2d for binomial models - in the case of the latter each row is interpreted as [success, failure].

```python
y = pd.get_dummies( possum["pop"], dtype="int")
X = pd.get_dummies( possum.drop(["site","pop"], axis=1), dtype="int")

res = sm.GLM(y, X, family = sm.families.Binomial(), missing="drop").fit()
print(res.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:       ['Vic', 'other']   No. Observations:                  102
Model:                            GLM   Df Residuals:                       95
Model Family:                Binomial   Df Model:                            6
Link Function:                  Logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -31.942
Date:                Tue, 24 Feb 2026   Deviance:                       63.885
Time:                        09:25:43   Pearson chi2:                     154.
No. Iterations:                     7   Pseudo R-squ. (CS):             0.5234
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
age            0.1373      0.183      0.751      0.453      -0.221       0.495
head_l        -0.1972      0.158     -1.247      0.212      -0.507       0.113
skull_w       -0.2001      0.139     -1.443      0.149      -0.472       0.072
total_l        0.7569      0.176      4.290      0.000       0.411       1.103
tail_l        -2.0698      0.429     -4.820      0.000      -2.912      -1.228
sex_f         40.0148     13.077      3.060      0.002      14.385      65.645
sex_m         38.5395     12.941      2.978      0.003      13.175      63.904
==============================================================================
```

Formula interface

```
res = smf.glm(
  "pop ~ sex + age + head_l + skull_w + total_l + tail_l-1",
  data = possum,
  family = sm.families.Binomial(),
  missing="drop"
).fit()
print(res.summary())
```

```
                 Generalized Linear Model Regression Results
=====================================================================================
Dep. Variable:     ['pop[Vic]', 'pop[other]']   No. Observations:                  102
Model:                                    GLM   Df Residuals:                       95
Model Family:                        Binomial   Df Model:                            6
Link Function:                          Logit   Scale:                          1.0000
Method:                                  IRLS   Log-Likelihood:                -31.942
Date:                        Tue, 24 Feb 2026   Deviance:                       63.885
Time:                                09:25:43   Pearson chi2:                     154.
No. Iterations:                             7   Pseudo R-squ. (CS):             0.5234
Covariance Type:                    nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
sex[f]        40.0148     13.077      3.060      0.002      14.385      65.645
sex[m]        38.5395     12.941      2.978      0.003      13.175      63.904
age            0.1373      0.183      0.751      0.453      -0.221       0.495
head_l        -0.1972      0.158     -1.247      0.212      -0.507       0.113
skull_w       -0.2001      0.139     -1.443      0.149      -0.472       0.072
total_l        0.7569      0.176      4.290      0.000       0.411       1.103
tail_l        -2.0698      0.429     -4.820      0.000      -2.912      -1.228
==============================================================================
```

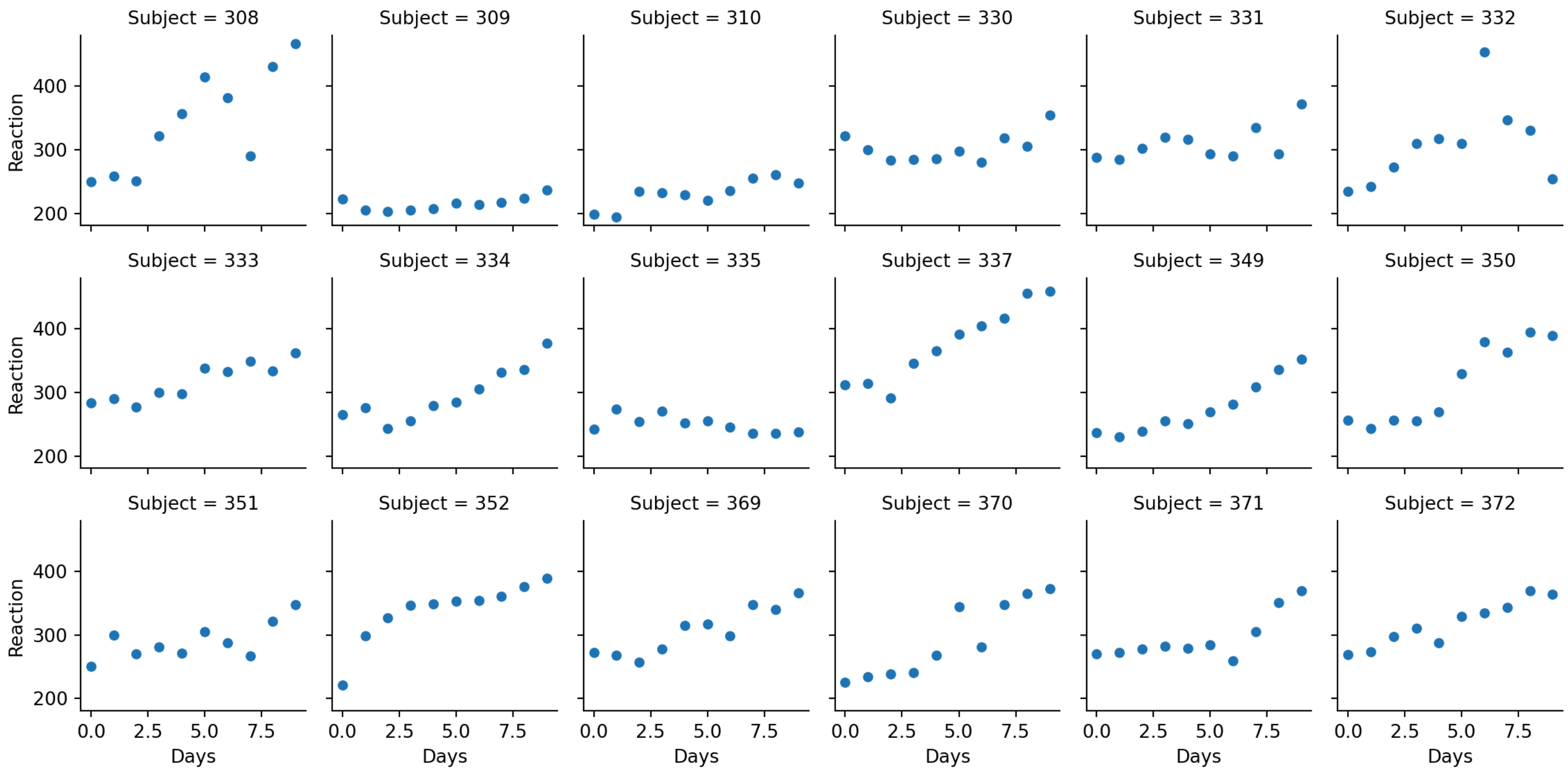
sleepstudy data

> These data are from the study described in Belenky et al. (2003), for the most sleep-deprived group (3 hours time-in-bed) and for the first 10 days of the study, up to the recovery period. The original study analyzed speed (1/(reaction time)) and treated day as a categorical rather than a continuous predictor.

```
sleep = pd.read_csv("data/sleepstudy.csv")
sleep
```

```
     Reaction  Days  Subject
0    249.5600     0      308
1    258.7047     1      308
2    250.8006     2      308
3    321.4398     3      308
4    356.8519     4      308
..        ...   ...      ...
175  329.6076     5      372
176  334.4818     6      372
177  343.2199     7      372
178  369.1417     8      372
179  364.1236     9      372

[180 rows x 3 columns]
```

```python
g = sns.relplot(x="Days", y="Reaction", col="Subject", col_wrap=6, data=sleep, height=2)
```



Random intercept model

```python
me_rand_int = smf.mixedlm(
  "Reaction ~ Days", data=sleep, groups=sleep["Subject"],
  subset=sleep.Days >= 2
)
res_rand_int = me_rand_int.fit(method=["lbfgs"])
print(res_rand_int.summary())
```

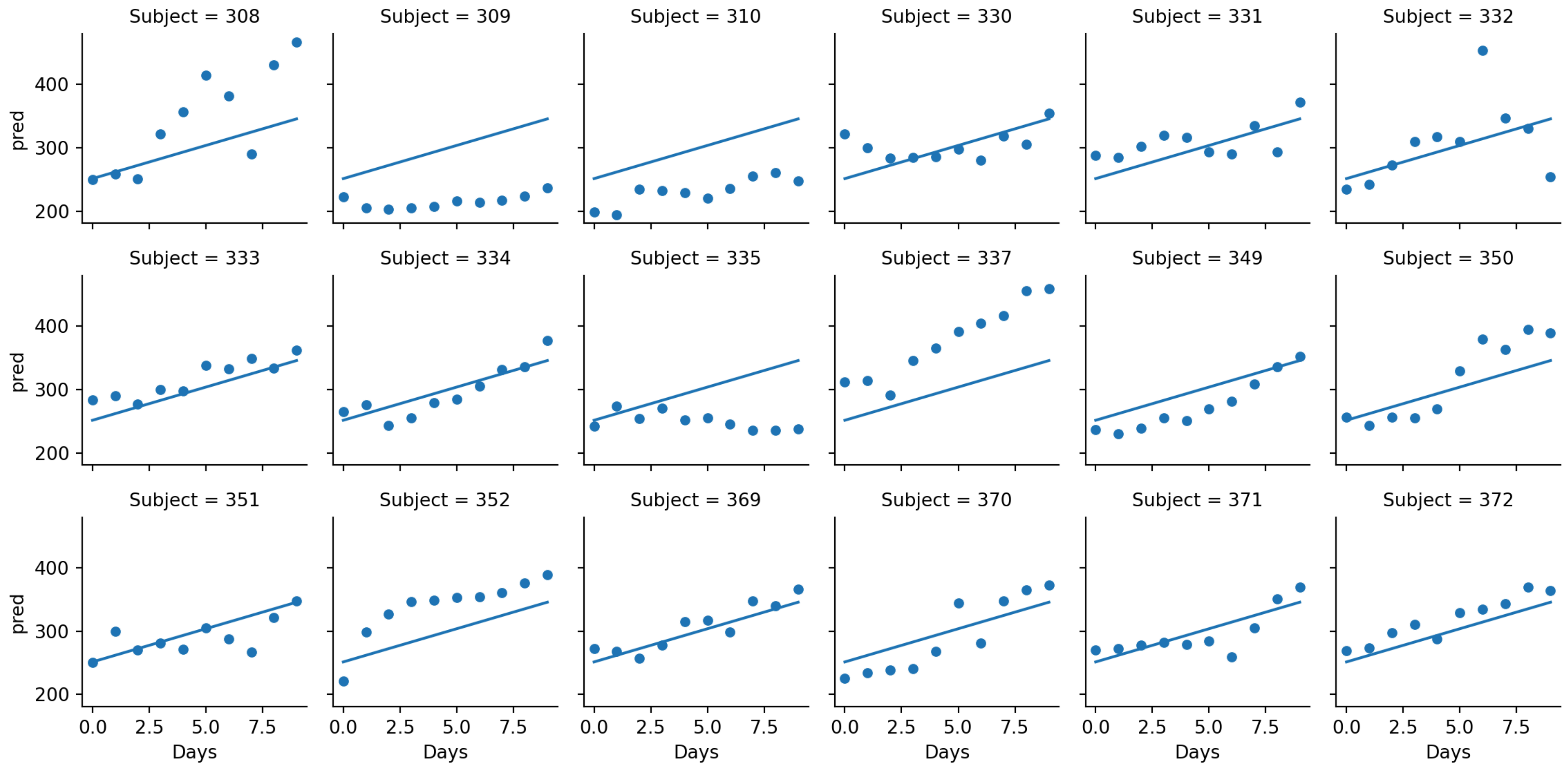
```
         Mixed Linear Model Regression Results
========================================================
Model:              MixedLM Dependent Variable: Reaction
No. Observations:   180     Method:             REML
No. Groups:         18      Scale:              960.4529
Min. group size:    10      Log-Likelihood:     -893.2325
Max. group size:    10      Converged:          Yes
Mean group size:    10.0
--------------------------------------------------------
           Coef.   Std.Err.   z    P>|z|  [0.025  0.975]
--------------------------------------------------------
Intercept  251.405    9.747 25.793 0.000 232.302 270.509
Days        10.467    0.804 13.015 0.000   8.891  12.044
Group Var 1378.232   17.157
========================================================
```

lme4 version

```r
summary(
  lmer(Reaction ~ Days + (1|Subject), data=sleepstudy)
)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: Reaction ~ Days + (1 | Subject)
   Data: sleepstudy

REML criterion at convergence: 1786.5

Scaled residuals:
    Min      1Q  Median      3Q     Max 
-3.2257 -0.5529  0.0109  0.5188  4.2506 

Random effects:
 Groups   Name        Variance Std.Dev.
 Subject  (Intercept) 1378.2   37.12   
 Residual              960.5   30.99   
Number of obs: 180, groups:  Subject, 18

Fixed effects:
            Estimate Std. Error t value
(Intercept) 251.4051     9.7467   25.79
Days         10.4673     0.8042   13.02

Correlation of Fixed Effects:
```

Predictions

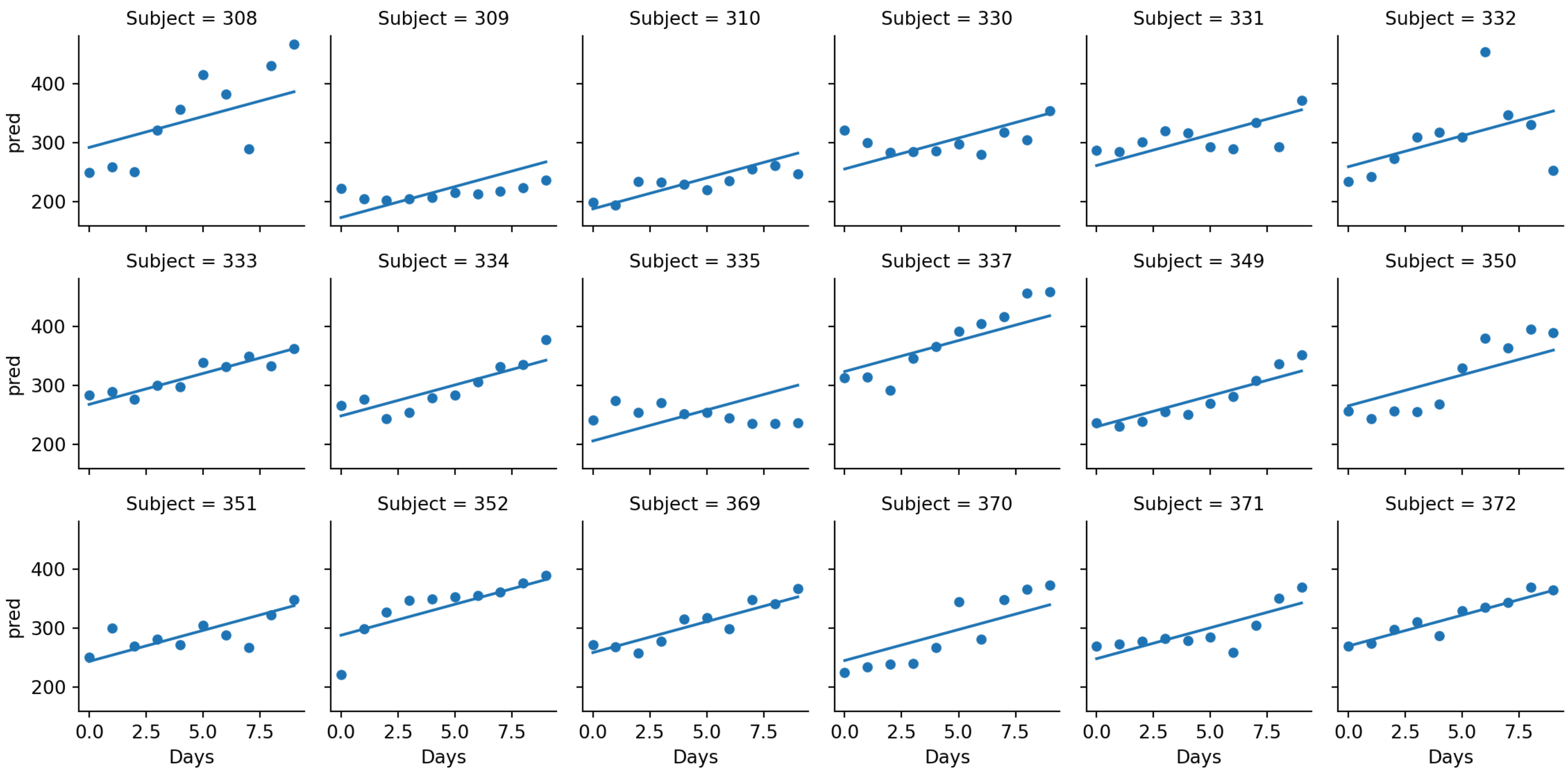


Recovering random effects for prediction

```
# Multiply each RE by the random effects design matrix for each group
rex = [
  np.dot(
    me_rand_int.exog_re_li[j],
    res_rand_int.random_effects[k]
  )
  for (j, k) in enumerate(me_rand_int.group_labels)
]
rex[0]
```

```
array([40.7838, 40.7838, 40.7838, 40.7838, 40.7838, 40.7838, 40.7838, 40.7838,
       40.7838, 40.7838])
```

```

# Add the fixed and random terms to get the overall prediction
y_hat = res_rand_int.predict() + np.concatenate(rex)
```


Subject = 308
Subject = 309
Subject = 310
Subject = 330
Subject = 331
Subject = 332
Subject = 333
Subject = 334
Subject = 335
Subject = 337
Subject = 349
Subject = 350
Subject = 351
Subject = 352
Subject = 369
Subject = 370
Subject = 371
Subject = 372
pred
Days
200
300
400
0.0
2.5
5.0
7.5

Random intercept and slope model

```
me_rand_sl= smf.mixedlm(
  "Reaction ~ Days", data=sleep, groups=sleep["Subject"],
  subset=sleep.Days >= 2,
  re_formula="~Days"
)
res_rand_sl = me_rand_sl.fit(method=["lbfgs"])
print(res_rand_sl.summary())
```

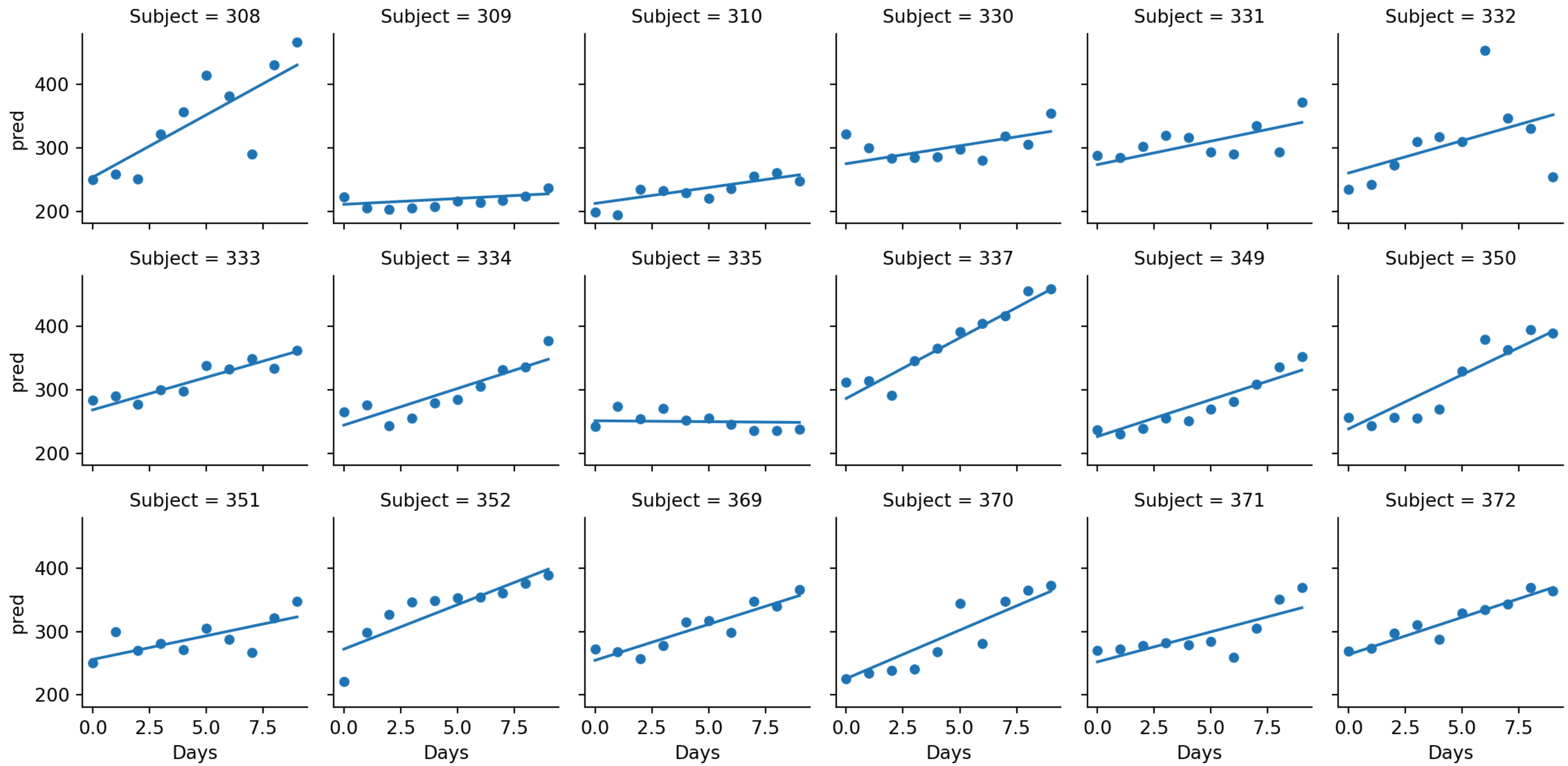
```
            Mixed Linear Model Regression Results
==============================================================
Model:                 MixedLM   Dependent Variable:   Reaction
No. Observations:      180       Method:               REML
No. Groups:            18        Scale:                654.9412
Min. group size:       10        Log-Likelihood:       -871.8141
Max. group size:       10        Converged:            Yes
Mean group size:       10.0
--------------------------------------------------------------
                  Coef.  Std.Err.   z    P>|z|  [0.025  0.975]
--------------------------------------------------------------
Intercept        251.405    6.825 36.838 0.000 238.029 264.781
Days              10.467    1.546  6.771 0.000   7.438  13.497
Group Var        612.089   11.881
Group x Days Cov   9.605    1.820
Days Var          35.072    0.610
==============================================================
```

lme4 version

```r
summary(
  lmer(Reaction ~ Days + (Days|Subject), data=sleepstudy)
)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: Reaction ~ Days + (Days | Subject)
   Data: sleepstudy

REML criterion at convergence: 1743.6

Scaled residuals: 
    Min      1Q  Median      3Q     Max 
-3.9536 -0.4634  0.0231  0.4634  5.1793 

Random effects:
 Groups   Name        Variance Std.Dev. Corr
 Subject  (Intercept) 612.10   24.741       
          Days         35.07    5.922   0.07
 Residual             654.94   25.592       
Number of obs: 180, groups:  Subject, 18

Fixed effects:
            Estimate Std. Error t value
(Intercept)  251.405      6.825  36.838
Days          10.467      1.546   6.771

Correlation of Fixed Effects:
     (Intr)
Days -0.138
```

Prediction



We are using the same approach described previously to obtain the RE estimates and use them in the predictions.