Pied PyPler

Why packaging is important for both open and close data science projects

Motivation

How many times did you...

- Looked for an old piece of code
- Searched Dropbox & private repos
- Started Jupyter to search notebooks
- **Gave up and rewritten it**

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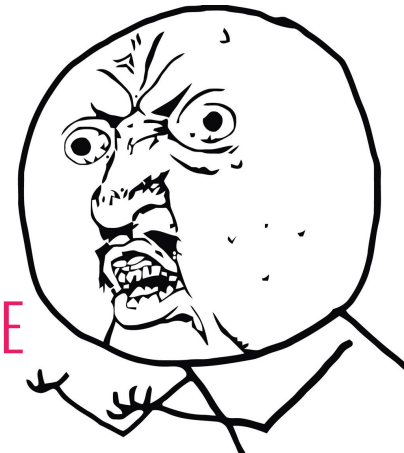

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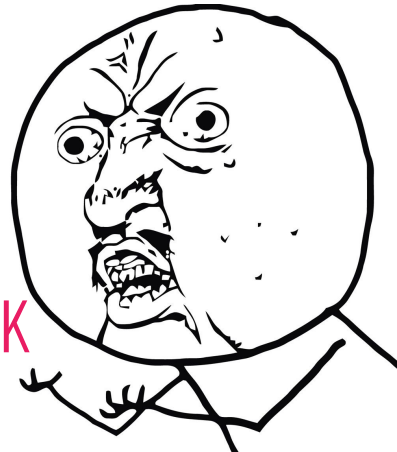

The solution?
Packaging!

What’s in it for me?

- Write **less code** (over time)
- Code is **used more**
- All shall love you and **despair**

What's in it for me?

- Wr
- Co
- All

What's in it for me?

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- All

ALSO, NO MATH!

You will learn:

- Benefits to your code
- Benefits to your colleagues
- Benefits to you
- Which DS code fits packaging
- Designing a simple Python package

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Benefits

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- Built-in incentive to:
  - **Simplify & clearify**
  - **Document**
  - **Test**
- Gains **developer scrutiny**

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AKA,

IT WORKS...

Benefits to people

- Code used **more often**, in more places
- **Other people** fixing & improving
- Manage **technical debt**
- Easier to **deploy**
- Save others writing it

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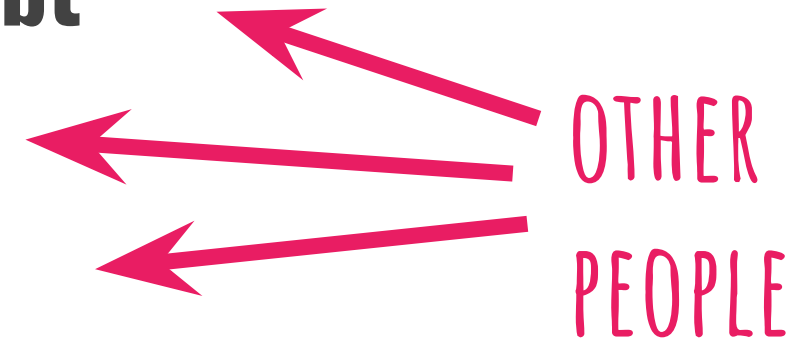

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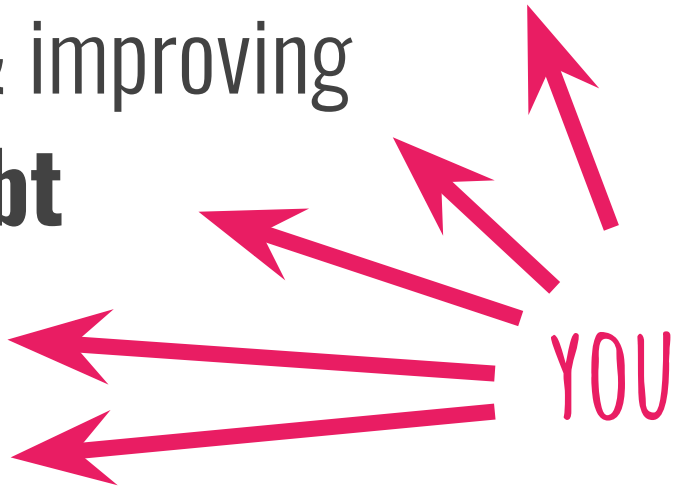

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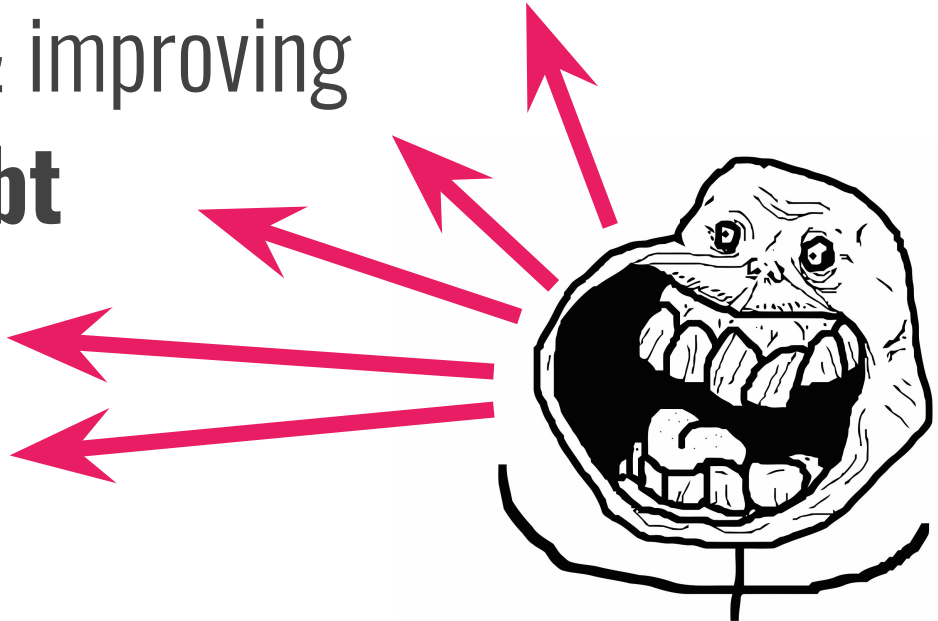

What to package?

Types of code worth packaging

- Extensions to existing libraries
- Adapting existing code to a common API
- Automatizing your flow
- Data science infrastructure
- Specific technique implementation

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imbutil

Additions to the `imbalanced-learn` package.

```
from imbutil.combine import MinMaxRandomSampler; from imblearn import pipeline;
# oversampling minority classes to 100 and undersampling majority classes to 800
sampler = MinMaxRandomSampler(min_freq=100, max_freq=800)
sampling_clf = pipeline.make_pipeline(sampler, inner_clf)
```

Contents

96 lines (83 sloc) | 3.44 KB

```python
"""Randomly samples data to bring all class frequencies into a range."""

import numpy as np
from sklearn.utils import check_X_y

from imblearn.base import SamplerMixin
from imblearn.utils import check_target_type, hash_X_y
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import RandomOverSampler


class MinMaxRandomSampler(SamplerMixin):
    """Random samples data to bring all class frequencies into a range.

    Parameters
```

```
class MinMaxRandomSampler(SamplerMixin):
    """Random samples data to bring all class frequencies into a range.

    Parameters
    ----------
    min_freq : int
        The minimum frequency for a class after sampling. All classes with
        fewer samples are over-sampled to have this number of samples.
    max_freq : int
        The maximum frequency for a class after sampling. All classes with
        more samples are under-sampled to have this number of samples.
    random_state : int, RandomState instance or None, optional (default=None)
        If int, random_state is the seed used by the random number generator;
        If RandomState instance, random_state is the random number generator;
        If None, the random number generator is the RandomState instance used
        by np.random.
    """
```

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skift

`scikit-learn` wrappers for Python `fastText`.

```
>>> from skift import FirstColFtClassifier
>>> df = pandas.DataFrame([['woof', 0], ['meow', 1]], columns=['txt', 'lbl'])
>>> sk_clf = FirstColFtClassifier(lr=0.3, epoch=10)
>>> sk_clf.fit(df[['txt']], df['lbl'])
>>> sk_clf.predict([['woof']])
[0]
```

Contents

```
"""scikit-learn classifier wrapper for fasttext."""

import os
import abc

import numpy as np
from fastText import train_supervised
from sklearn.base import BaseEstimator, ClassifierMixin
from sklearn.utils.multiclass import unique_labels
from sklearn.exceptions import NotFittedError

from .util import (
    temp_dataset_fpath,
    dump_xy_to_fasttext_format,
    python_fasttext_model_to_bytes,
    bytes_to_python_fasttext_model,
)


class FtClassifierABC(BaseEstimator, ClassifierMixin, metaclass=abc.ABCMeta):
```

Return ndarrays instead of lists while predicting #2

Closed **uniaz** opened this issue on Mar 13 · 4 comments

uniaz commented on Mar 13 Contributor

The functions `predict`, `predict_proba` return `lists` instead of `numpy` arrays which makes them unusable with classifiers like `sklearn.multiclass.OneVsRestClassifier`. `GridSearch` and other similar functionality also don't work.

This is a quick fix.

8 skift/core.py View

```
@@ -156,10 +156,10 @@ def predict(self, X):
156 156         y : array of int of shape = [n_samples]
157 157             Predicted labels for the given inpurt samples.
158 158         """
159     -       return [
    159 +       return np.array([
160 160             self._clean_label(res[0][0])
161 161             for res in self._predict(X)
162     -       ]
    162 +       ], dtype=np.float_)
163 163
164 164     def _format_probas(self, result):
165 165         lbl_prob_pairs = zip(result[0], result[1])
@@ -181,10 +181,10 @@ def predict_proba(self, X):
181 181             The class probabilities of the input samples. The order of the
182 182             classes corresponds to that in the attribute classes_.
183 183         """
184     -       return [
    184 +       return np.array([
185 185             self._format_probas(res)
186 186             for res in self._predict(X, self.num_classes_)
187     -       ]
    187 +       ], dtype=np.float_)
```

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pdpipe

Easy pipelines for pandas DataFrames.

```
>>> df = pd.DataFrame(
        data=[[4, 165, 'USA'], [2, 180, 'UK'], [2, 170, 'Greece']],
        index=['Dana', 'Jane', 'Nick'],
        columns=['Medals', 'Height', 'Born']
    )
>>> pipeline = pdp.ColDrop('Medals').Binarize('Born')
>>> pipeline(df)
          Height  Born_UK  Born_USA
    Dana     165        0         1
    Jane     180        1         0
    Nick     170        0         0
```

3.2.2 Printing Pipelines

A pipeline structre can be clearly displayed by printing the object:

```
>>> drop_name = pdp.ColDrop("Name")
>>> binar_label = pdp.Binarize("Label")
>>> map_job = pdp.MapColVals("Job", {"Part": True, "Full":True, "No": False})
>>> pipeline = pdp.PdPipeline([drop_name, binar_label, map_job])
>>> print(pipeline)
A pdpipe pipeline:
[ 0]  Drop column Name
[ 1]  Binarize Label
[ 2]  Map values of column Job with {'Part': True, 'Full': True, 'No': False}.
```

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barn

Simple local/remote dataset store for Python.

```
from barn import Dataset
twitter_usa = Dataset(name='twitter_usa', task='NER')
# download from an azure block blob storage and load into a dataframe
twitter_usa.download(tags=['preprocessed'], version='20180305')
df = twitter_usa.df(tags=['preprocessed'], version='20180305')
```

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Build text classification models

See tests/ folder for usage.

NOT MY PACKAGE!

Word based models

When dataset represented as `(docs, words)` word based models can be created using `TokenI`

```
from keras_text.models import TokenModelFactory
from keras_text.models import YoonKimCNN, AttentionRNN, StackedRNN


# RNN models can use `max_tokens=None` to indicate variable length words per mini-
factory = TokenModelFactory(1, tokenizer.token_index, max_tokens=100, embedding_t
word_encoder_model = YoonKimCNN()
model = factory.build_model(token_encoder_model=word_encoder_model)
model.compile(optimizer='adam', loss='categorical_crossentropy')
model.summary()
```

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How to package?

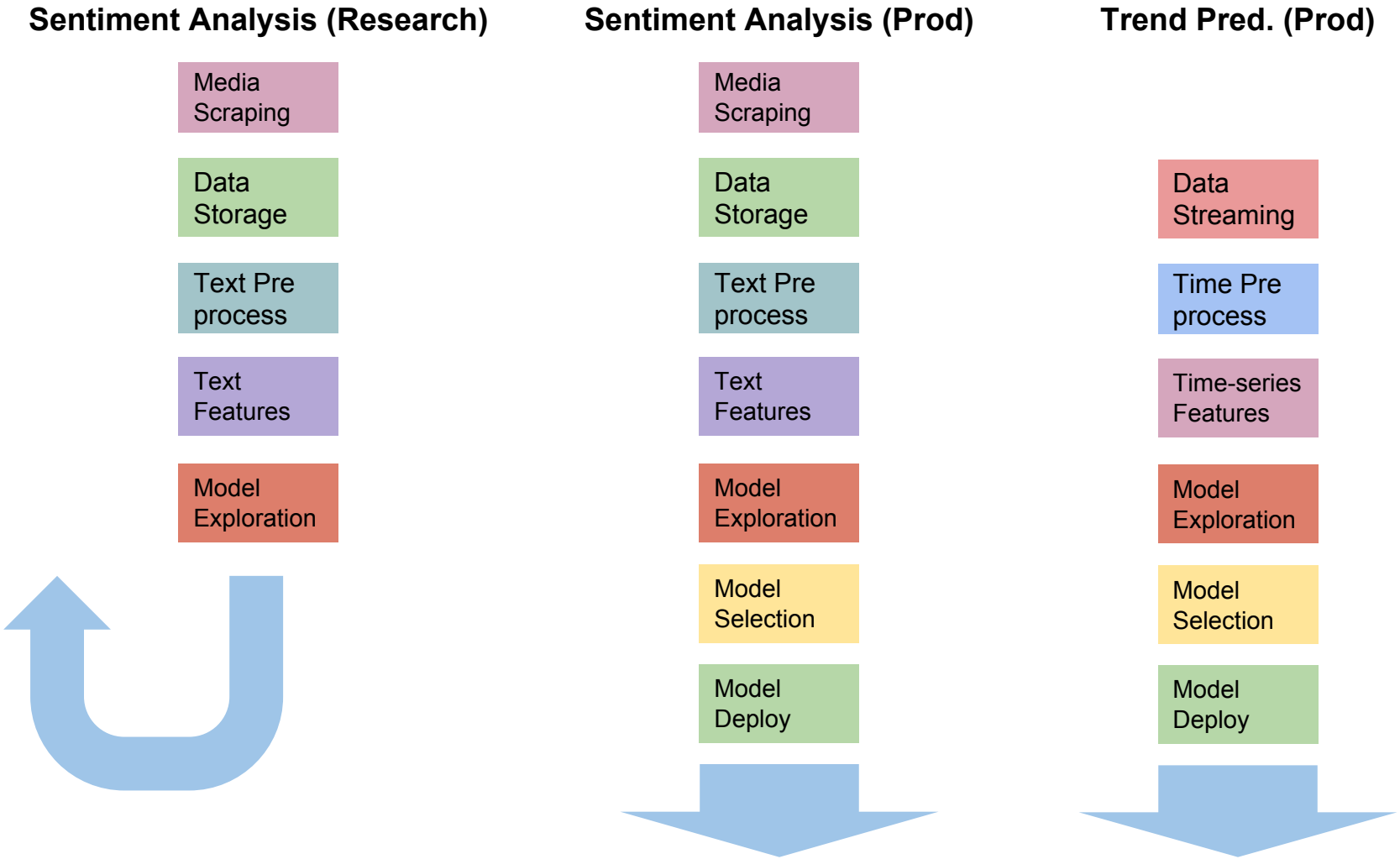
Good practices

- Do one thing
- Generalize the use case
- Keep it simple
- Advertise professionalism

Do one thing

- NO: Data processing + model deployment + feature selection
- Don’t recreate a flow; rather, a slice.

  (horizontal, not vertical)


Sentiment Analysis (Research)
Media Scraping
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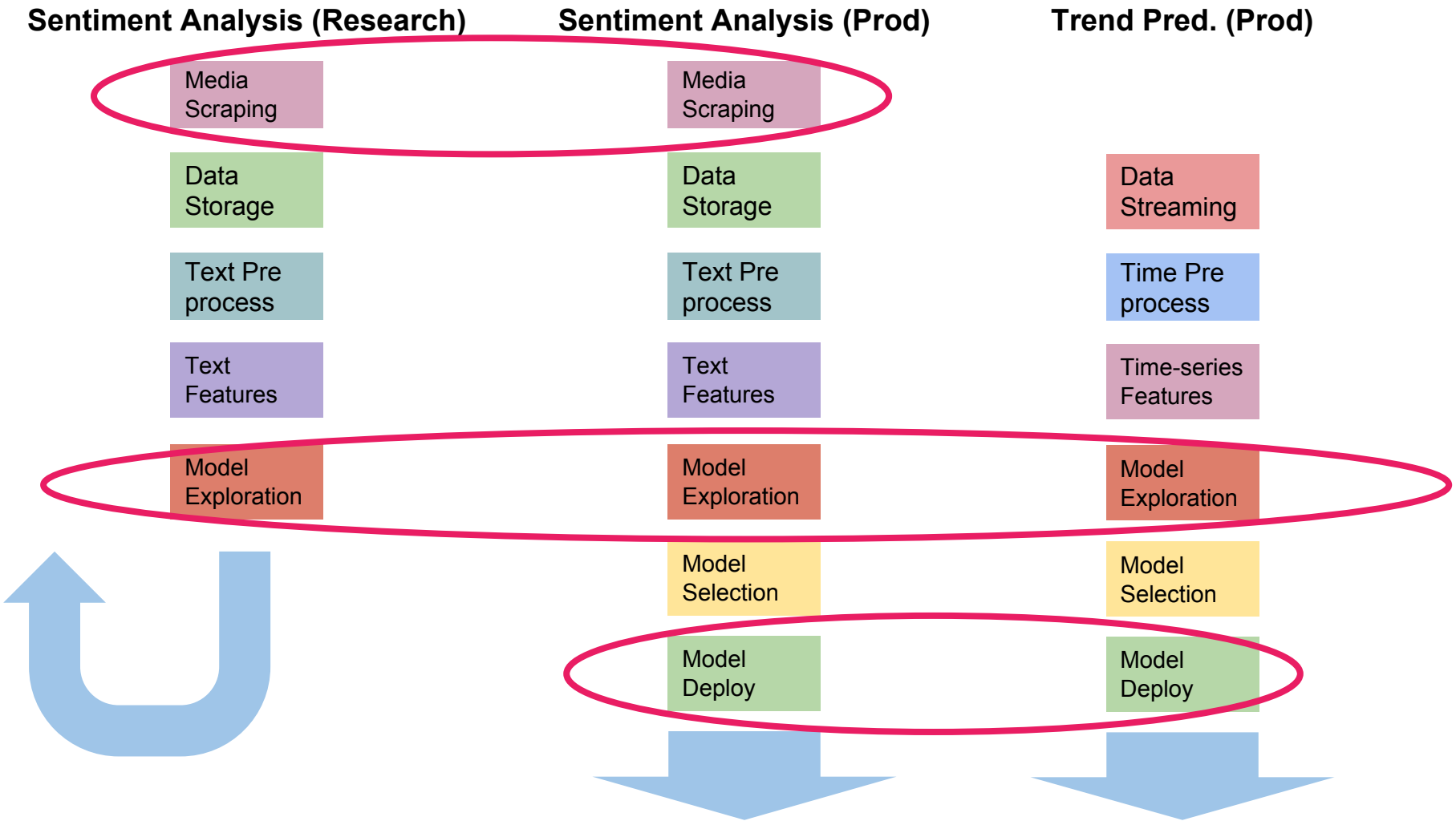
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Model Deploy
Data Streaming
Time Pre process
Time-series Features
Model Exploration
Model Selection
Model Deploy

Generalize the use case

- Parameterize
- Split when X ways forward
  - If it’s not too much work...

3.1 Standard wrappers

These wrappers do not make additional assumptions on input besides those commonly made by `scikit-learn` classifies; i.e. that input is a 2d `ndarray` object and such.

- `FirstColFtClassifier` - An sklearn classifier adapter for fasttext that takes the first column of input `ndarray` objects as input.
- `IdxBasedFtClassifier` - An sklearn classifier adapter for fasttext that takes input by column index. This is set on object construction by providing the `input_ix` parameter to the constructor.

3.2 pandas-dependent wrappers

These wrappers assume the `X` parameter given to `fit`, `predict`, and `predict_proba` methods is a `pandas.DataFrame` object:

- `FirstObjFtClassifier` - An sklearn adapter for fasttext using the first column of `dtype == object` as input.
- `ColLblBasedFtClassifier` - An sklearn adapter for fasttext taking input by column label. This is set on object construction by providing the `input_col_lbl` parameter to the constructor.

```python
@abc.abstractmethod
def _input_col(self, X):
    pass  # pragma: no cover
```

`FirstColFtClassifier`

```python
class FirstColFtClassifier(FtClassifierABC):
    """An sklearn classifier adapter for fast

    Parameters
    ----------
    **kwargs
        Additional keyword arguments will be
        fasttext.train_supervised.
    """

    def _input_col(self, X):
        return np.array(X)[:, 0]
```

`FirstObjFtClassifier`

```python
def _input_col(self, X):
    input_col_name = None
    for col_name, dtype in X.dtypes.items():
        if dtype == object:
            input_col_name = col_name
            break
    if input_col_name is not None:
        return X[input_col_name]
    raise ValueError("No object dtype column in input param X.")
```

Keep it simple

- Informative class/function names
- Minimal API
- A clear example with one/two imports

```
>>> from skift import FirstColFtClassifier
>>> df = pandas.DataFrame([['woof', 0], ['meow', 1]], columns=['txt', 'lbl'])
>>> sk_clf = FirstColFtClassifier(lr=0.3, epoch=10)
>>> sk_clf.fit(df[['txt']], df['lbl'])
>>> sk_clf.predict([['woof']])
[0]
```

```
from skutil.estimators import ColumnIgnoringClassifier
# use a classifier that can't handle string data as
# an inner classifier in some stacked model, for example
```

```
>>> df = pd.DataFrame(
        data=[[4, 165, 'USA'], [2, 180, 'UK'], [2, 170, 'Greece']],
        index=['Dana', 'Jane', 'Nick'],
        columns=['Medals', 'Height', 'Born']
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>>> pipeline = pdp.ColDrop('Medals').Binarize('Born')
>>> pipeline(df)
          Height  Born_UK  Born_USA
    Dana     165        0         1
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```

Advertise professionalism

- Continuous testing
- Test coverage
- Permissive License
- Documentation
- Encourage contributions

pdpipe

Easy pipelines for pandas DataFrames.

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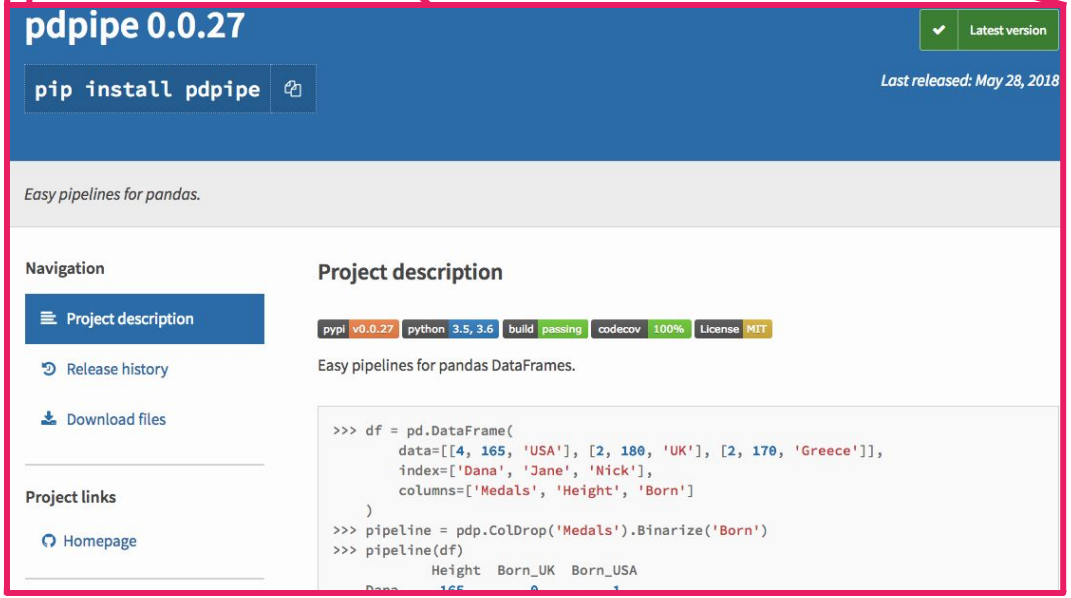

pdpipe

pypi v0.0.27 | python 3.5, 3.6 | build passing | codecov 100% | License MIT

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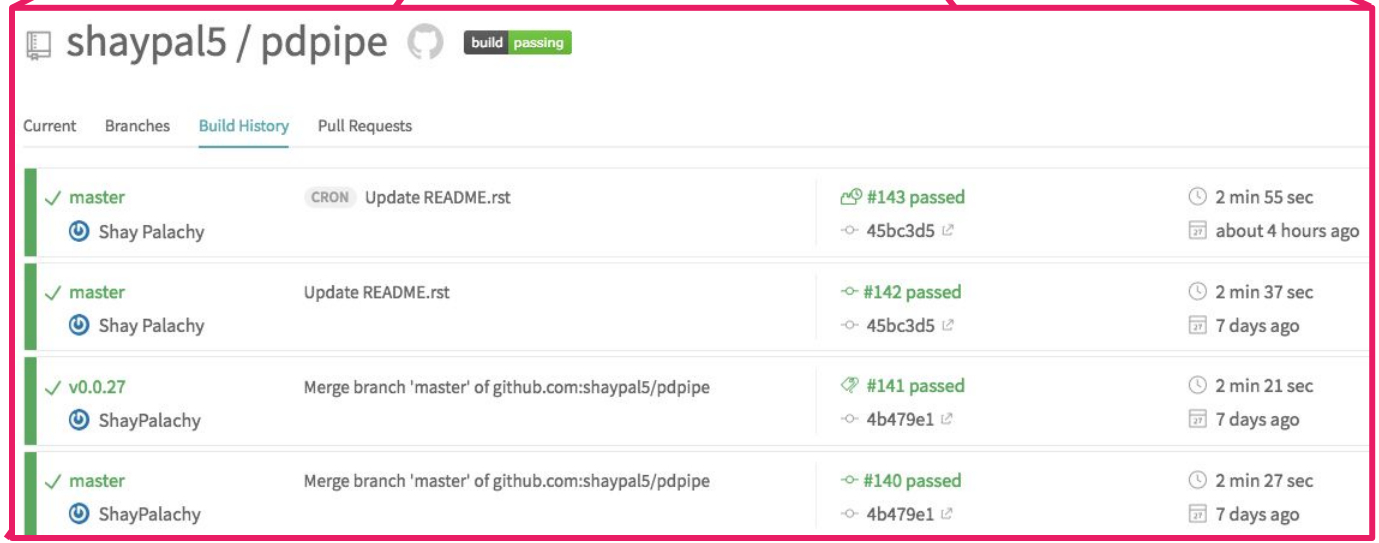

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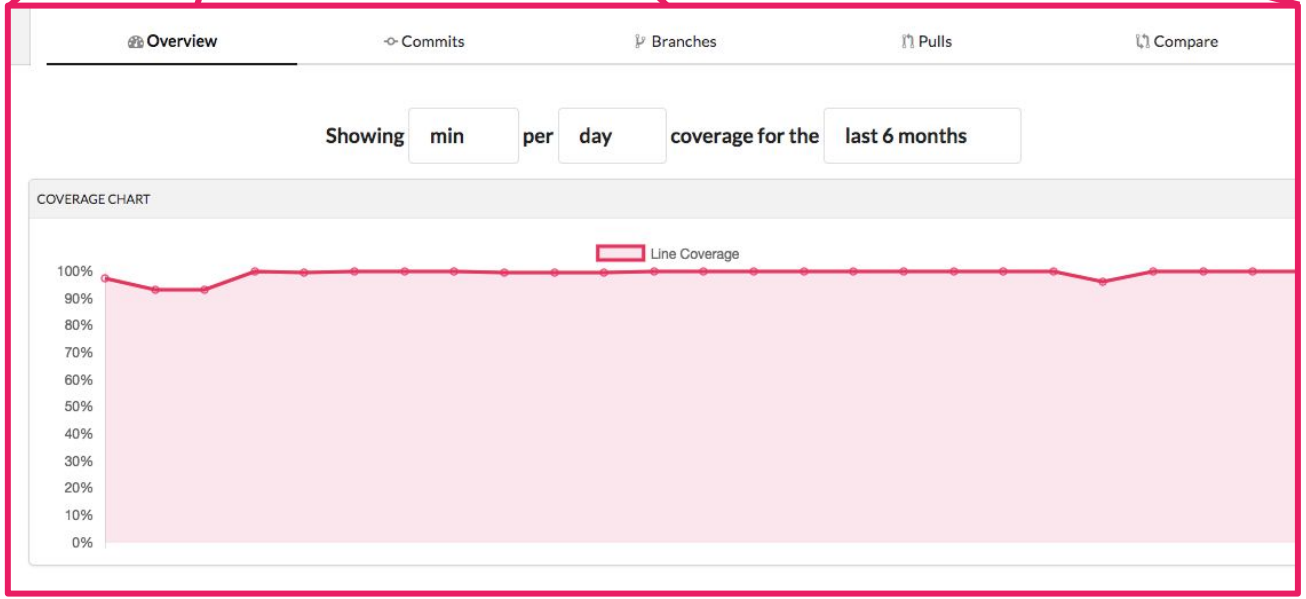

Contents

6 Contributing

Package author and current maintainer is Shay Palachy (shay.palachy@gmail.com); You are more than welcome to approach him for help. Contributions are very welcomed, especially since this package is very much in its infancy and many other pipeline stages can be added.

6.1 Installing for development

Clone:

```
git clone git@github.com:shaypal5/pdpipe.git
```

Install in development mode with test dependencies:

```
cd pdpipe
pip install -e ".[test]"
```

6.2 Running the tests

To run the tests, use:

```
python -m pytest --cov=pdpipe
```

6.3 Adding documentation

This project is documented using the numpy docstring conventions, which were chosen as they are perhaps the most widely-spread conventions that are both supported by common tools such as Sphinx and result in human-readable docstrings (in my personal opinion, of course). When documenting code you add to this project, please follow these conventions.

Good practices

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What’s next?

Homework

Example repo:
https://github.com/shaypal5/catlolzer

- Go home
- Find code you can package
- Create & upload a first version
- **Email me** at shay.palachy@gmail.com
- I'll help (if needed)

Homework

- Go to you company
- Deploy a private PyPI server
- Create & upload a first version
- People catch up surprisingly fast
- **Email me** at shay.palachy@gmail.com

That’s it!

Email me at shay.palachy@gmail.com