Python tools for Machine Learning

Dr. Amilcar Soares



Summary



- Pandas
- The animals tracking dataset
- Scikit-learn
- Assignment
- Extra challenge Trajectory visualization

Pandas (1)



Pandas consists of:

- A set of labeled array data structures, the primary of which are Series and DataFrames
- Index objects enabling both simple axis indexing and multi-level / hierarch indexing
- An integrated group by engine for aggregating and transforming data sets
- Input/Output tools: loading tabular data from flat files (CSV, delimited, Excel saving and loading pandas objects from the fast and efficient PyTables/HDF5 format.
- Memory-efficient "sparse" versions of the standard data structures for storion mostly missing or mostly constant (some fixed value)
- Moving window statistics (rolling mean, rolling standard deviation, etc.)

...

Pandas (2)



Data structures

Dimensions	Name
1	Series
2	DataFrame
3	Panel

The best way to think about the pandas data structures is as **flexible containers** for lower dimensional data. For example, DataFrame is a container for Series, and Panel is a container for DataFrame objects. We would like to **be able** to **insert** and **remove objects from these containers** in a dictionary-like fashion.

Pandas (3)



DataFrames

 DataFrame is a 2-dimensional labeled data structure with columns of potential types. You can think of it like a spreadsheet or SQL table, or a dict of Series objects.

```
In [32]: d = {'one' : pd.Series([1., 2., 3.], index=['a', 'b', 'c']),
   'two': pd.Series([1., 2., 3., 4.], index=['a', 'b', 'c', 'd'])]
   . . . . :
In [33]: df = pd.DataFrame(d)
In [34]: df
Out[34]:
  one
       two
  1.0
      1.0
  2.0
      2.0
  3.0 3.0
  NaN
      4.0
```

Pandas (4)



DataFrames:

```
In [56]: df['one']
Out[56]:
    1.0
     2.0
    3.0
    NaN
Name: one, dtype: float64
In [57]: df['three'] = df['one'] * df['two']
In [58]: df['flag'] = df['one'] > 2
In [59]: df
Out[59]:
   one two three
                    flag
       1.0
                   False
  1.0
              1.0
   2.0
       2.0
              4.0 False
       3.0
              9.0
                    True
       4.0
  NaN
              NaN
                   False
```

```
In [72]: iris.assign(sepal ratio = lambda x: (x['SepalWidth'] /
                                               x['SepalLength'])).head()
   ....:
   . . . . :
Out[72]:
   SepalLength SepalWidth PetalLength PetalWidth
                                                             Name
                                                                    sepal ratio
           5.1
                       3.5
                                                 0.2 Iris-setosa
                                                                         0.6863
                                     1.4
           4.9
                       3.0
                                     1.4
                                                 0.2 Iris-setosa
                                                                         0.6122
           4.7
                       3.2
                                                 0.2 Iris-setosa
                                                                         0.6809
                                     1.3
           4.6
                       3.1
                                     1.5
                                                      Iris-setosa
                                                                         0.6739
           5.0
                       3.6
                                     1.4
                                                 0.2 Iris-setosa
                                                                         0.7200
```

Pandas (5)



DataFrames (TimeSeries) - DateTimeIndex

```
In [1]: dates = pd.date_range('1/1/2000', periods=8)
In [2]: df = pd.DataFrame(np.random.randn(8, 4), index=dates, columns=['A', 'B', 'C', 'D'])
```

Property	Description
year	The year of the datetime
month	The month of the datetime
day	The days of the datetime
hour	The hour of the datetime
minute	The minutes of the datetime
second	The seconds of the datetime
microsecond	The microseconds of the datetime
nanosecond	The nanoseconds of the datetime
date	Returns datetime.date (does not contain timezone information)
time	Returns datetime.time (does not contain timezone information)
dayofyear	The ordinal day of year
weekofyear	The week ordinal of the year
week	The week ordinal of the year
dayofweek	The number of the day of the week with Monday=0, Sunday=6
weekday	The number of the day of the week with Monday=0, Sunday=6
weekday_name	The name of the day in a week (ex: Friday)
quarter	Quarter of the date: Jan-Mar = 1, Apr-Jun = 2, etc.
days_in_month	The number of days in the month of the datetime
is_month_start	Logical indicating if first day of month (defined by frequency)
is_month_end	Logical indicating if last day of month (defined by frequency)
is_quarter_start	Logical indicating if first day of quarter (defined by frequency)
is_quarter_end	Logical indicating if last day of quarter (defined by frequency)
is_year_start	Logical indicating if first day of year (defined by frequency)
is_year_end	Logical indicating if last day of year (defined by frequency)
is_leap_year	Logical indicating if the date belongs to a leap year

Pandas (6)



DataFrames (Multi-Indexing)

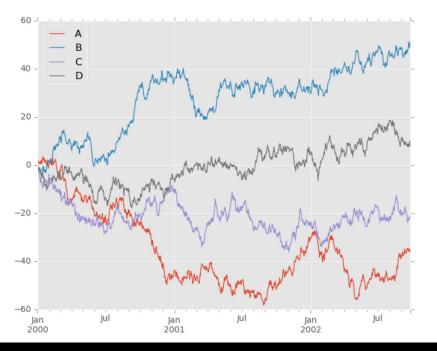
```
In [10]: arrays = [np.array(['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux']),
                   np.array(['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two'])]
   . . . . :
In [11]: s = pd.Series(np.random.randn(8), index=arrays)
In [12]: s
Out[12]:
           -0.861849
bar one
         -2.104569
     two
baz one
         -0.494929
          1.071804
     two
           0.721555
foo one
     two
           -0.706771
gux one
           -1.039575
            0.271860
     two
dtype: float64
In [13]: df = pd.DataFrame(np.random.randn(8, 4), index=arrays)
In [14]: df
Out[14]:
bar one -0.424972 0.567020 0.276232 -1.087401
    two -0.673690 0.113648 -1.478427 0.524988
baz one 0.404705 0.577046 -1.715002 -1.039268
    two -0.370647 -1.157892 -1.344312 0.844885
foo one 1.075770 -0.109050 1.643563 -1.469388
    two 0.357021 -0.674600 -1.776904 -0.968914
qux one -1.294524 0.413738 0.276662 -0.472035
    two -0.013960 -0.362543 -0.006154 -0.923061
```

Pandas (7)



- Data Visualization
 - TimeSeries

```
In [5]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=list('ABCD'))
In [6]: df = df.cumsum()
In [7]: plt.figure(); df.plot();
```

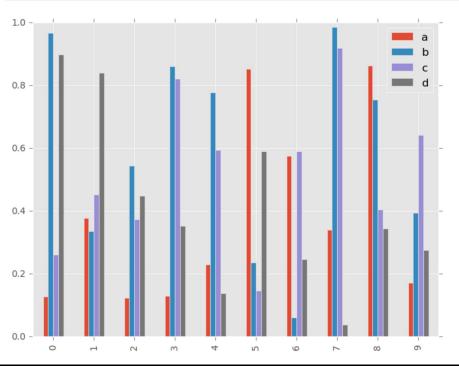


Pandas (8)



- Data Visualization
 - Bar chart

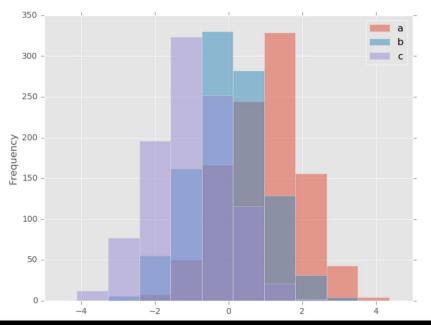




Pandas (9)

Institute for Big Data Analytics

- Data Visualization
 - Histograms

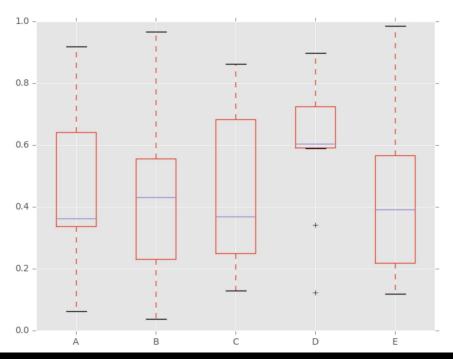


Pandas (10)



- Data Visualization
 - **Boxplots**

```
In [34]: df = pd.DataFrame(np.random.rand(10, 5), columns=['A', 'B', 'C', 'D', 'E'])
In [35]: df.plot.box()
Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x13534fcf8>
```

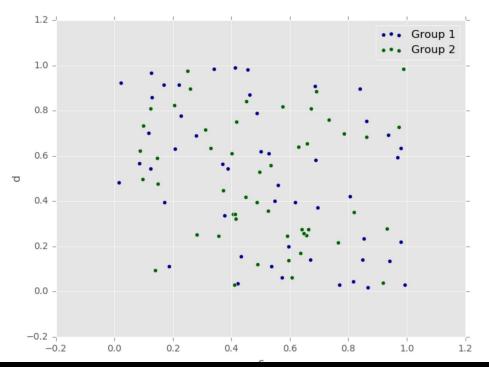


Pandas (11)



- Data Visualization
 - Scatter plots

```
In [62]: ax = df.plot.scatter(x='a', y='b', color='DarkBlue', label='Group 1');
In [63]: df.plot.scatter(x='c', y='d', color='DarkGreen', label='Group 2', ax=ax);
```

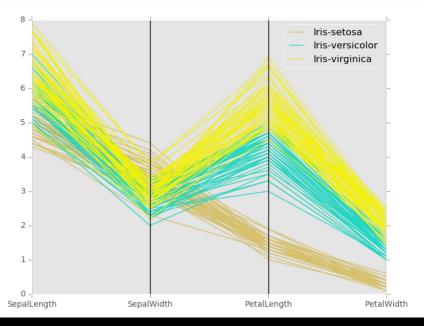


Pandas (11)

Institute for Big Data Analytics

- Data Visualization
 - Parallel coordinates

```
In [89]: from pandas.plotting import parallel_coordinates
In [90]: data = pd.read_csv('data/iris.data')
In [91]: plt.figure()
Out[91]: <matplotlib.figure.Figure at 0x13212da90>
In [92]: parallel_coordinates(data, 'Name')
Out[92]: <matplotlib.axes._subplots.AxesSubplot at 0x12da44da0>
```



The animals tracking dataset (1)



• The Starkey Project







Pictures from starkey project



Cattle



Deer



Elk

Pictures from web: Cattle -

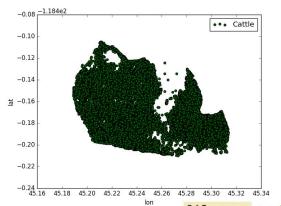
https://fm.cnbc.com/applications/cnbc.com/resources/img/editorial/2014/01/29/101374915-186501746.530x298.jpg?y=1485533269

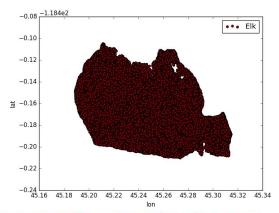
Deer - http://qfp.sd.gov/hunting/big-game/images/deer1-01.jpg
Elk - https://elknetwork.com/wp-content/uploads/2016/09/bull elk.jpg

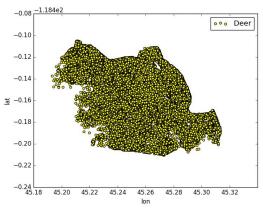
The animals tracking dataset (2)



- Plot geographical data points with pandas
 - Warning: This is not the proper way. The points are not projected.







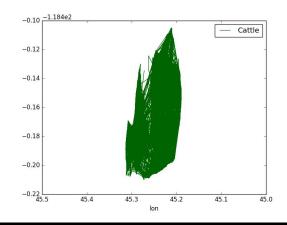
```
filename = './input/cattle_visualization.txt'
col_names = ['id', 'time', 'lon', 'lat', 'spd']
df = pd.read_csv(filename, names=col_names, sep=',', index_col=False)

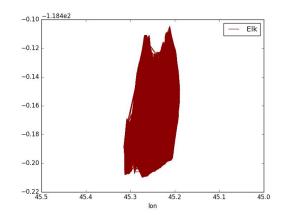
df.plot.scatter(x='lon', y='lat', color='DarkGreen', label='Cattle')
plt.savefig('./images/cattle points.png')
```

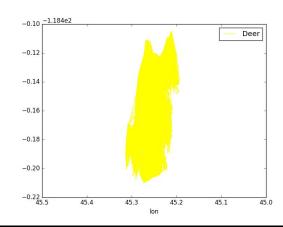
The animals tracking dataset (3)



```
x_ticks = [45.0, 45.1, 45.2, 45.3, 45.4, 45.5]
filename = './input/cattle_visualization.txt'
df = pd.read_csv(filename, names=['id', 'time', 'lon', 'lat', 'spd'],sep=',',parse_dates=[1])
df.plot.line(x='lon',y='lat', color='DarkGreen', label='Cattle', xticks=x_ticks)
plt.savefig('./images/cattle-linestring.png')
filename = './input/elk_visualization.txt'
df = pd.read_csv(filename, names=['id', 'time', 'lon', 'lat', 'spd'],sep=',',parse_dates=[1])
df.plot.line(x='lon',y='lat', color='DarkRed', label='Elk', xticks=x_ticks)
plt.savefig('./images/elk-linestring.png')
filename = './input/deer_visualization.txt'
df = pd.read_csv(filename, names=['id', 'time', 'lon', 'lat', 'spd'],sep=',',parse_dates=[1])
df.plot.line(x='lon',y='lat', color='Yellow', label='Deer', xticks=x_ticks)
plt.savefig('./images/deer-linestring.png')
```







The animals tracking dataset (4)



Computation of point features.

```
# get the last index of an animal
# this prevents calculating wrong distances across two different animals
def get masks(df):
  ids = df.id.unique()
  print(str(len(ids))+" unique animals in total.")
  ids list = np.array(df.id)
  mask = [0 if i==(len(ids list)-1) or ids list[i]!=ids list[i+1] else 1 for i in range(len(ids list))]
def get timediff(df):
  timediff = [(df.time[i+1]-df.time[i]).total_seconds() if i!=(len(df.time)-1) else 0 for i in range(len(df.time))]
  timediff = [timediff[i]*mask[i] for i in range(len(timediff))]
  df['timediff']=timediff
  return df
  distance = [qpxpy.qeo.haversine distance(df.lat[i], df.lon[i], df.lat[i+1], df.lon[i+1]) if i!=(len(df.time)-1) else 0 for i in range(len(df.time))]
  distance = [distance[i]*mask[i] for i in range(len(distance))]
  df['distance']=distance
  return df
def get speed(df):
  speed = [df.distance[i]/(df.timediff[i]+0.1**10) for i in range(len(df.time))]
  speed = [speed[i]*mask[i] for i in range(len(speed))]
  df['speed']= speed
  return df
def get_acc(df):
  acc = [(df.speed[i+1]-df.speed[i])/(df.timediff[i]+0.1**10) if i!=(len(df.time)-1) else 0 for i in range(len(df.time))]
  acc = [acc[i]*mask[i] for i in range(len(acc))]
  df['acc']= acc
  return df
def get bearing(df):
  bearing = [calculate_initial_compass_bearing((df.lat[i], df.lon[i]), (df.lat[i+1], df.lon[i+1])) if i!=(len(df.time)-1) else 0 for i in range(len(df.time))]
  bearing = [bearing[i]*mask[i] for i in range(len(bearing))]
  df['bearing']=bearing
  return df
```

```
data = read_file()
mask = get_masks(data)
data = get_timediff(data)
data = get_distance(data)
data = get_speed(data)
data = get_acc(data)
data = get_bearing(data)

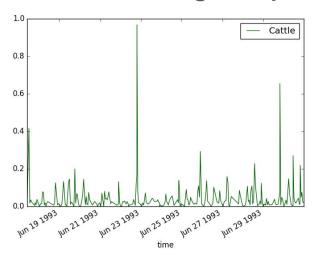
data = get_bearing(data)

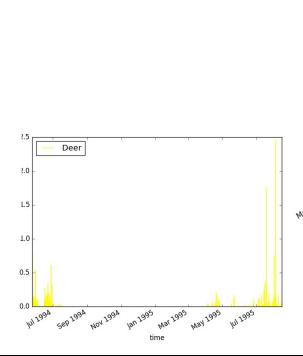
data = data.round{{'distance': 2, 'speed': 2, 'acc': 2, 'bearing': 2, 'timediff': 2}})
data = data.query('speed <= 20. and acc <= 100. and acc >= -100.')
print data.head()
data.to_csv(out_filename)
```

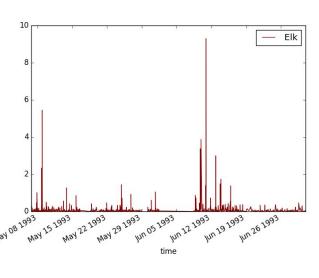
The animals tracking dataset (5)



Visualizing the speed along the trajectory







The animals tracking dataset (6)



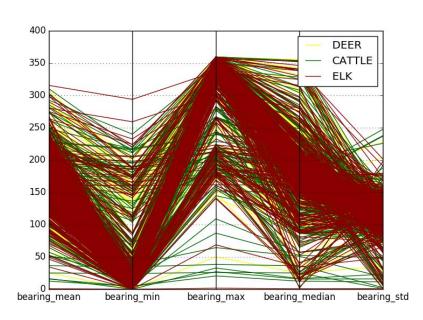
From points sequence to trajectories.

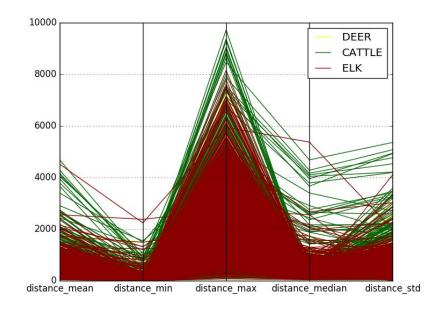
```
data = read file(f['filename'])
all trais = pd.DataFrame()
out = open(f['out filename'], 'w')
#process by trajectory id to avoid a high memory usage
for id in data.id.unique():
    t = data[data['id'] == id]
    t.time = pd.to datetime(t.time)
    slice = t[['time', 'timediff','distance','speed','acc','bearing']].set_index('time').resample('W')
    means = slice.mean()
    means.columns = ['timediff_mean','distance_mean','speed_mean','acc_mean','bearing_mean']
    amin = slice.min()
    amin.columns = ['timediff_min', 'distance_min', 'speed_min', 'acc_min', 'bearing_min']
    amax = slice.max()
    amax.columns = ['timediff max', 'distance max', 'speed max', 'acc max', 'bearing max']
    amedian = slice.median()
    amedian.columns = ['timediff median', 'distance median', 'speed median', 'acc median', 'bearing median']
    astd = slice.std()
    astd.columns = ['timediff_std', 'distance_std', 'speed_std', 'acc_std', 'bearing_std']
    subtrais = pd.concat([means, amin], axis=1)
    subtrajs = pd.concat([subtrajs, amax], axis=1)
    subtrais = pd.concat([subtrais. amedian], axis=1)
    subtrais = pd.concat([subtrais, astd], axis=1)
    subtrajs['class'] = f['cls']
    all trajs = all trajs.append(subtrajs)
all_trajs = all_trajs.dropna(axis=0, how='any')
print all trais.head()
all trajs.to csv(f['out filename'], index=False)
all trajs.to csv('./output/animals.csv', header=False, index=False, mode='a')
```

The animals tracking dataset (7)



Plotting some parallels coordinates





Scikit-learn (1)



- Machine learning for applications
 - Ease of use
 - Light and easy to install package

State-of-the-art algorithms

High quality bindings: performance and fine control

- Open Source
 - BSD license

Scikit-learn (2)



• Scikit-learn.org



Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.

Algorithms: SVM, nearest neighbors, random forest, ... — Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices. **Algorithms**: SVR, ridge regression, Lasso,

... — Examples

Clustering

Automatic grouping of similar objects into

Applications: Customer segmentation, Grouping experiment outcomes

Algorithms: k-Means, spectral clustering, mean-shift, ... — Examples

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency

Algorithms: PCA, feature selection, non-negative matrix factorization. — Examples

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning

Modules: grid search, cross validation, metrics.

— Examples

Preprocessing

Feature extraction and normalization.

Application: Transforming input data such as text for use with machine learning algorithms.

Modules: preprocessing, feature extraction.

- Examples

Scikit-learn (3)



- All objects
 - estimator.fit(X train, y train)
- Classification, regression, clustering
 - o y_pred = estimator.predict(X_test)
- Filters, dimension reduction, latent variables
 - X_new = estimator.transform(X_test)
- Predictive models, density estimation
 - o test_score = estimator.score(X_test)
- On-line learning
 - estimator.refit(X_train, y_train)

Scikit-learn (4)



Pre-processing (reading csv)

```
data = pd.read_csv(filename, names=col_names, sep=',', index_col=False)
data = data.values

train = np.array(data[:,:25])
# print 'Train', train

target = np.array(data[:, -1:])
# print 'Target', target
```

Binarize the classes

```
# transform targets

target_a = [0 if target[i] == 'A' else 1 for i in range(len(target))]
target_b = [0 if target[i] == 'B' else 1 for i in range(len(target))]
target_c = [0 if target[i] == 'C' else 1 for i in range(len(target))]
```

Scikit-learn (5)



Predict and score

```
from sklearn.tree.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score

X_train, X_test, y_train, y_test = train_test_split(train, true_labels, random_state=0)

clf = DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
print confusion_matrix(y_test, y_pred)
print accuracy_score(y_test, y_pred)
```

References



- Pandas
 - https://pandas.pydata.org/pandas-docs/stable/index.html

- Trajectory Dataset
 - https://www.fs.fed.us/pnw/starkey/

- Scikit-learn
 - http://scikit-learn.org/stable/