homework3

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1 Homework 3: Classifiers

1.0.1 Objectives

Follow the TODOs and read through and understand the provided code. For this assignment you will work with extracting different types of labels, constructing predictive classifier models from these labels, and evaluating the generalized performance of these models. Additionally, it is good practice to have a high level understanding of the data one is working with, thus upon loading the data the info and summary statistics are also displayed, in addition to the head, tail, and whether there are any NaNs.

This assignment utilizes code examples from the lecture on classifiers

- Pipelines
- Classification
  - Label extraction and construction
  - Prediction
  - Performance Evaluation
  - Utilization of Cross Validation
- Do not save work within the ml_practices folder
  - create a folder in your home directory for assignments, and copy the templates there

1.0.2 General References

- Python Built-in Functions
- Python Data Structures
- Numpy Reference
- Summary of matplotlib
- Pandas DataFrames
- Sci-kit Learn Linear Models
  - SGDClassifier
- Sci-kit Learn Ensemble Models
- Sci-kit Learn Metrics
- Sci-kit Leatn Model Selection

[1]:
```
import pandas as pd
import numpy as np
import os, re, fnmatch
import matplotlib.pyplot as plt
import matplotlib.patheffects as peffects

from sklearn.pipeline import Pipeline
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn.metrics import mean_squared_error, confusion_matrix, roc_curve, auc
from sklearn.linear_model import SGDClassifier
from sklearn.ensemble import GradientBoostingClassifier


FIGWIDTH = 6
FIGHEIGHT = 6
FONTSIZE = 12

plt.rcParams['figure.figsize'] = (FIGWIDTH, FIGHEIGHT)
plt.rcParams['font.size'] = FONTSIZE

plt.rcParams['xtick.labelsize'] = FONTSIZE
plt.rcParams['ytick.labelsize'] = FONTSIZE

%matplotlib inline
```

2 LOAD DATA

[2]:
```
""" TODO
Load data from subject k2 for week 05
Display info() for the data

These are data obtained from a baby on the SIPPC. 3D Position (i.e. kinematic)
data are collected at 50 Hz, for the x, y, and z positions in meters, for␣
 ↪various
joints such as the wrists, elbows, shoulders, etc.
"""
fname = 'ml_practices/imports/datasets/baby1/subject_k2_w05.csv'# TODO
baby_data_raw = pd.read_csv(fname)# TODO
baby_data_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15000 entries, 0 to 14999
Data columns (total 43 columns):
```

```
time               15000 non-null float64
left_wrist_x       14987 non-null float64
left_wrist_y       14987 non-null float64
left_wrist_z       14987 non-null float64
right_wrist_x      14984 non-null float64
right_wrist_y      14984 non-null float64
right_wrist_z      14984 non-null float64
left_elbow_x       15000 non-null float64
left_elbow_y       15000 non-null float64
left_elbow_z       15000 non-null float64
right_elbow_x      15000 non-null float64
right_elbow_y      15000 non-null float64
right_elbow_z      15000 non-null float64
left_shoulder_x    15000 non-null float64
left_shoulder_y    15000 non-null float64
left_shoulder_z    15000 non-null float64
right_shoulder_x   15000 non-null float64
right_shoulder_y   15000 non-null float64
right_shoulder_z   15000 non-null float64
left_knee_x        15000 non-null float64
left_knee_y        15000 non-null float64
left_knee_z        15000 non-null float64
right_knee_x       15000 non-null float64
right_knee_y       15000 non-null float64
right_knee_z       15000 non-null float64
left_ankle_x       15000 non-null float64
left_ankle_y       15000 non-null float64
left_ankle_z       15000 non-null float64
right_ankle_x      15000 non-null float64
right_ankle_y      15000 non-null float64
right_ankle_z      15000 non-null float64
left_foot_x        15000 non-null float64
left_foot_y        15000 non-null float64
left_foot_z        15000 non-null float64
right_foot_x       15000 non-null float64
right_foot_y       15000 non-null float64
right_foot_z       15000 non-null float64
upper_back_x       15000 non-null float64
upper_back_y       15000 non-null float64
upper_back_z       15000 non-null float64
sippc_action       15000 non-null float64
robot_vel_l        15000 non-null float64
robot_vel_r        15000 non-null float64
dtypes: float64(43)
memory usage: 4.9 MB
```

[3]:
```python
""" TODO
Display the first few examples
"""

baby_data_raw.head(5)
```

[3]:
```
   time  left_wrist_x  left_wrist_y  left_wrist_z  right_wrist_x  \
0  0.00      0.220415      0.181230     -0.129179       0.234461
1  0.02      0.221667      0.180757     -0.128407       0.233129
2  0.04      0.222194      0.180795     -0.127102       0.231888
3  0.06      0.222396      0.181160     -0.126370       0.230835
4  0.08      0.223019      0.182199     -0.124856       0.230171

   right_wrist_y  right_wrist_z  left_elbow_x  left_elbow_y  left_elbow_z  \
0      -0.235074      -0.058906      0.172050      0.227567     -0.052032
1      -0.237052      -0.058938      0.173125      0.227220     -0.051447
2      -0.238736      -0.058754      0.173883      0.227297     -0.050020
3      -0.240115      -0.058329      0.174341      0.227243     -0.048877
4      -0.241552      -0.058468      0.174702      0.227184     -0.046883

   …  left_foot_z  right_foot_x  right_foot_y  right_foot_z  upper_back_x  \
0  …    -0.117939     -0.214891     -0.051161     -0.248173      0.225993
1  …    -0.123085     -0.215723     -0.051426     -0.248049      0.226178
2  …    -0.122420     -0.217153     -0.052046     -0.247054      0.226289
3  …    -0.121519     -0.218098     -0.052721     -0.246157      0.226414
4  …    -0.122356     -0.219171     -0.053410     -0.244805      0.226513

   upper_back_y  upper_back_z  sippc_action  robot_vel_l  robot_vel_r
0      0.012226      0.021536           0.0    -0.000181     0.004893
1      0.011346      0.021050           0.0    -0.000178     0.004820
2      0.010714      0.020789           0.0    -0.000175     0.004748
3      0.010120      0.020412           0.0    -0.000173     0.004677
4      0.009397      0.020212           0.0    -0.000170     0.004609

[5 rows x 43 columns]
```

[4]:
```python
""" TODO
Display the last few examples
"""

baby_data_raw.tail(5)
```

[4]:
```
         time  left_wrist_x  left_wrist_y  left_wrist_z  right_wrist_x  \
14995  299.90      0.305730      0.168831      0.033561       0.259778
14996  299.92      0.305648      0.167093      0.034346       0.260100
14997  299.94      0.306012      0.165883      0.035369       0.260067
14998  299.96      0.306393      0.165342      0.036705       0.260300
```

```
14999  299.98      0.307053      0.165342      0.038167       0.260593

       right_wrist_y  right_wrist_z  left_elbow_x  left_elbow_y  left_elbow_z  \
14995      -0.171445       0.045665      0.238274      0.244787      0.044443
14996      -0.170313       0.046645      0.239116      0.243905      0.044899
14997      -0.169648       0.047763      0.240050      0.243200      0.045813
14998      -0.169104       0.048301      0.240694      0.242808      0.047692
14999      -0.168929       0.048783      0.241236      0.242589      0.049956

       …  left_foot_z  right_foot_x  right_foot_y  right_foot_z  \
14995  …    -0.212863     -0.072385     -0.137549     -0.260178
14996  …    -0.213741     -0.071297     -0.136961     -0.260497
14997  …    -0.214687     -0.070472     -0.136552     -0.260672
14998  …    -0.215449     -0.070135     -0.136213     -0.260645
14999  …    -0.215919     -0.070001     -0.136121     -0.260579

       upper_back_x  upper_back_y  upper_back_z  sippc_action  robot_vel_l  \
14995      0.192844      0.022664      0.080014           8.0     0.001891
14996      0.192431      0.022375      0.080498           8.0     0.001887
14997      0.192087      0.022130      0.080898           8.0     0.001884
14998      0.191871      0.021943      0.081155           8.0     0.001880
14999      0.191652      0.021846      0.081390           8.0     0.001878

       robot_vel_r
14995     0.055393
14996     0.055518
14997     0.055618
14998     0.055695
14999     0.055752

[5 rows x 43 columns]
```

[5]:
```python
""" TODO
Display the summary statistics
"""

baby_data_raw.describe()
```

[5]:
```
               time  left_wrist_x  left_wrist_y  left_wrist_z  right_wrist_x  \
count  15000.000000  14987.000000  14987.000000  14987.000000   14984.000000
mean     149.990000      0.244686      0.125995     -0.016250       0.222374
std       86.605427      0.049269      0.102700      0.096238       0.060946
min        0.000000      0.083382     -0.034872     -0.177069       0.106451
25%       74.995000      0.220651      0.027081     -0.119591       0.170334
50%      149.990000      0.249578      0.126924     -0.010748       0.202907
75%      224.985000      0.270780      0.227609      0.073604       0.283243
max      299.980000      0.370966      0.320520      0.154593       0.329078
```

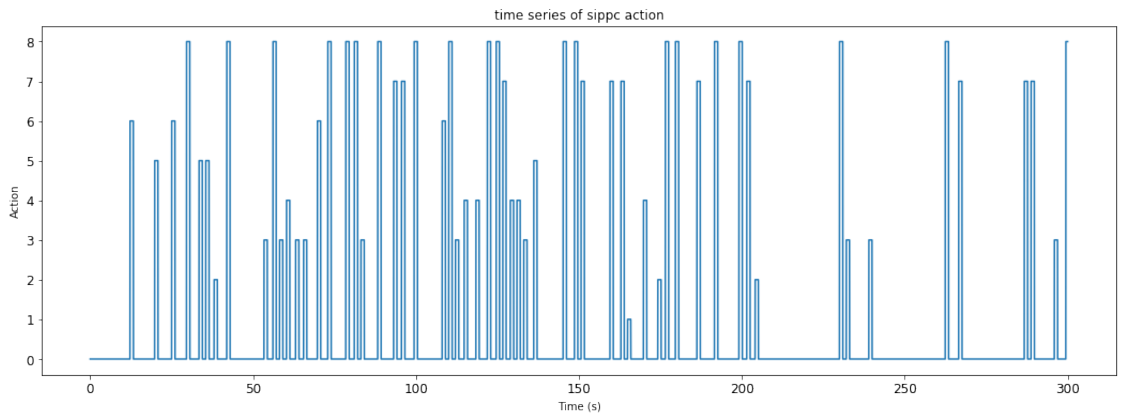
```
       right_wrist_y  right_wrist_z  left_elbow_x  left_elbow_y  left_elbow_z  \
count   14984.000000   14984.000000  15000.000000  15000.000000  15000.000000
mean       -0.153784      -0.021553      0.203240      0.157987      0.002500
std         0.042294       0.045206      0.046069      0.062485      0.052760
min        -0.274525      -0.124859      0.110774      0.064651     -0.092058
25%        -0.177999      -0.060396      0.161956      0.098481     -0.050258
50%        -0.137865      -0.027056      0.201472      0.140740      0.020384
75%        -0.125323       0.011331      0.247348      0.222750      0.035858
max        -0.071355       0.151956      0.284781      0.260276      0.176419

       …   left_foot_z  right_foot_x  right_foot_y  right_foot_z  \
count  …  15000.000000  15000.000000  15000.000000  15000.000000
mean   …     -0.228861     -0.073937     -0.050101     -0.235308
std    …      0.067573      0.097112      0.045566      0.028536
min    …     -0.327945     -0.256544     -0.160185     -0.297654
25%    …     -0.285460     -0.164332     -0.088158     -0.254496
50%    …     -0.248474     -0.028150     -0.048895     -0.241090
75%    …     -0.177103      0.012705     -0.017788     -0.215172
max    …      0.000970      0.035922      0.089456     -0.140069

       upper_back_x  upper_back_y  upper_back_z  sippc_action  robot_vel_l  \
count  15000.000000  15000.000000  15000.000000  15000.000000  15000.000000
mean       0.183821     -0.025163      0.065818      1.143400     -0.000345
std        0.026734      0.046388      0.020480      2.498917      0.004045
min        0.133454     -0.092531      0.011274      0.000000     -0.014122
25%        0.162355     -0.069502      0.052854      0.000000     -0.001392
50%        0.174270     -0.046750      0.070823      0.000000     -0.000036
75%        0.209942      0.022537      0.080999      0.000000      0.000716
max        0.226768      0.047361      0.104098      8.000000      0.016195

        robot_vel_r
count  15000.000000
mean       0.003076
std        0.028319
min       -0.074040
25%       -0.012675
50%        0.001257
75%        0.019756
max        0.077659

[8 rows x 43 columns]
```

[6]:
```python
""" TODO
Check the dataframe for any NaNs using pandas methods
isna() and any() for a summary of the missing data
"""
```

```python
pd.isna(baby_data_raw).any()
```

[6]:
```
time                 False
left_wrist_x          True
left_wrist_y          True
left_wrist_z          True
right_wrist_x         True
right_wrist_y         True
right_wrist_z         True
left_elbow_x         False
left_elbow_y         False
left_elbow_z         False
right_elbow_x        False
right_elbow_y        False
right_elbow_z        False
left_shoulder_x      False
left_shoulder_y      False
left_shoulder_z      False
right_shoulder_x     False
right_shoulder_y     False
right_shoulder_z     False
left_knee_x          False
left_knee_y          False
left_knee_z          False
right_knee_x         False
right_knee_y         False
right_knee_z         False
left_ankle_x         False
left_ankle_y         False
left_ankle_z         False
right_ankle_x        False
right_ankle_y        False
right_ankle_z        False
left_foot_x          False
left_foot_y          False
left_foot_z          False
right_foot_x         False
right_foot_y         False
right_foot_z         False
upper_back_x         False
upper_back_y         False
upper_back_z         False
sippc_action         False
robot_vel_l          False
robot_vel_r          False
dtype: bool
```

[7]:
```python
""" TODO
Plot the sippc actions over time for the original dataset
"""
time = baby_data_raw.time# TODO
action = baby_data_raw.sippc_action# TODO

# TODO: Plot
plt.figure(figsize=(FIGWIDTH*3, FIGHEIGHT))
# TODO: complete this plot of time vs action
plt.xlabel("Time (s)")
plt.ylabel("Action")
plt.plot(time, action);
plt.title('time series of sippc action')
plt.show()
```



3 Data Selection

[8]:
```python
""" PROVIDED
"""
## Support for identifying kinematic variable columns
def get_kinematic_properties(data):
    # Regular expression for finding kinematic fields
    regx = re.compile("_[xyz]$")

    # Find the list of kinematic fields
    fields = list(data)
    fieldsKin = [x for x in fields if regx.search(x)]
    return fieldsKin

def position_fields_to_velocity_fields(fields, prefix='d_'):
    '''
```

```
    Given a list of position columns, produce a new list
    of columns that include both position and velocity
    '''
    fields_new = [prefix + x for x in fields]
    return fields + fields_new
```

[9]:
```
""" PROVIDED
Get the names of the sets of fields for the kinematic features and the
velocities
"""
fieldsKin = get_kinematic_properties(baby_data_raw)
fieldsKinVel = position_fields_to_velocity_fields(fieldsKin)
print(fieldsKinVel)
```

```
['left_wrist_x', 'left_wrist_y', 'left_wrist_z', 'right_wrist_x',
'right_wrist_y', 'right_wrist_z', 'left_elbow_x', 'left_elbow_y',
'left_elbow_z', 'right_elbow_x', 'right_elbow_y', 'right_elbow_z',
'left_shoulder_x', 'left_shoulder_y', 'left_shoulder_z', 'right_shoulder_x',
'right_shoulder_y', 'right_shoulder_z', 'left_knee_x', 'left_knee_y',
'left_knee_z', 'right_knee_x', 'right_knee_y', 'right_knee_z', 'left_ankle_x',
'left_ankle_y', 'left_ankle_z', 'right_ankle_x', 'right_ankle_y',
'right_ankle_z', 'left_foot_x', 'left_foot_y', 'left_foot_z', 'right_foot_x',
'right_foot_y', 'right_foot_z', 'upper_back_x', 'upper_back_y', 'upper_back_z',
'd_left_wrist_x', 'd_left_wrist_y', 'd_left_wrist_z', 'd_right_wrist_x',
'd_right_wrist_y', 'd_right_wrist_z', 'd_left_elbow_x', 'd_left_elbow_y',
'd_left_elbow_z', 'd_right_elbow_x', 'd_right_elbow_y', 'd_right_elbow_z',
'd_left_shoulder_x', 'd_left_shoulder_y', 'd_left_shoulder_z',
'd_right_shoulder_x', 'd_right_shoulder_y', 'd_right_shoulder_z',
'd_left_knee_x', 'd_left_knee_y', 'd_left_knee_z', 'd_right_knee_x',
'd_right_knee_y', 'd_right_knee_z', 'd_left_ankle_x', 'd_left_ankle_y',
'd_left_ankle_z', 'd_right_ankle_x', 'd_right_ankle_y', 'd_right_ankle_z',
'd_left_foot_x', 'd_left_foot_y', 'd_left_foot_z', 'd_right_foot_x',
'd_right_foot_y', 'd_right_foot_z', 'd_upper_back_x', 'd_upper_back_y',
'd_upper_back_z']
```

4 Construct Pipeline Components

[10]:
```
""" PROVIDED
"""
# Pipeline component: select subsets of attributes
class DataFrameSelector(BaseEstimator, TransformerMixin):
    def __init__(self, attribs):
        self.attribs = attribs
    def fit(self, x, y=None):
        return self
```

```
    def transform(self, X):
        return X[self.attribs]

# Pipeline component: drop all rows that contain invalid values
class DataSampleDropper(BaseEstimator, TransformerMixin):
    def __init__(self):
        pass
    def fit(self, x, y=None):
        return self
    def transform(self, X):
        return X.dropna(how='any')

# Pipeline component: Compute derivatives
class ComputeDerivative(BaseEstimator, TransformerMixin):
    def __init__(self, attribs, dt=1.0, prefix='d_'):
        self.attribs = attribs
        self.dt = dt
        self.prefix = prefix
    def fit(self, x, y=None):
        return self
    def transform(self, X):
        # Compute derivatives
        Xout = X.copy()
        for field in self.attribs:
            # Extract the values for this field
            values = Xout[field].values
            # Compute the difference between subsequent values
            diff = values[1:] - values[0:-1]
            # Bring the length to be the same as original data
            np.append(diff, 0)
            # Name of the new field
            name = self.prefix + field
            Xout[name] = pd.Series(diff / self.dt)
        return Xout
```

5 Construct Pipelines

[11]:
```
""" PROVIDED
Create four pipelines.
The first pipeline computes the derivatives of select features
within the dataframe and then drops rows containing NaNs.
The second pipeline extracts the kinematic and velocity (derivative)
features from the dataframe.
The third pipeline extracts the time from the dataframe.
The fourth pipeline extracts the sippc_action from the dataframe.
```

```python
"""
# Sampling rate: number of seconds between each time sample
dt = .02

# Initial pre-processing
pipe0 = Pipeline([
    ('derivative', ComputeDerivative(fieldsKin, dt=dt)),
    ('dropper', DataSampleDropper())
])

# Position, velocity selector
pipe_kin_vel = Pipeline([
    ('selector', DataFrameSelector(fieldsKinVel))
])

# Time selector
pipe_time = Pipeline([
    ('selector', DataFrameSelector(['time']))
])

# Action selector
pipe_action = Pipeline([
    ('selector', DataFrameSelector(['sippc_action']))
])
```

5.1 Pre-process and extract data

[12]:
```python
""" TODO
Use the pipelines to extract the data with kinematic and velocity features,
the time, and the sippc actions.
See the lecture on classifers for examples
"""
# TODO: use the first pipeline to perform and initial cleaning of the data
baby_data_prcd = pipe0.transform(baby_data_raw)# TODO

# TODO: Use the result from the first pipeline to get the kinematic and
#       velocity features by using the pipe_kin_vel pipeline
data_pos_vel = pipe_kin_vel.transform(baby_data_prcd)# TODO

# TODO: Use the result from the first pipeline to get the time by using
#       the pipe_time pipeline
data_time = pipe_time.transform(baby_data_prcd)# TODO

# TODO: Use the result from the first pipeline to get the action by using
#       the pipe_action pipeline
data_action = pipe_action.transform(baby_data_prcd)# TODO
```

```
# PROVIDED: Get the dataframes as numpy arrays
inputs_pos_vel = data_pos_vel.values
time = data_time.values
action = data_action.values

nsamples = action.shape[0]
nsamples
```

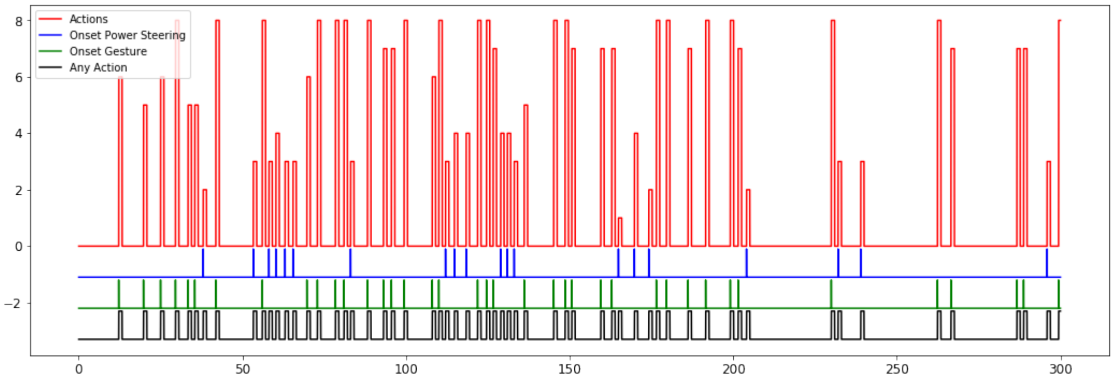
[12]: 14941

5.2 Observing and Obtaining Labels

[13]:
```
""" PROVIDED
Extract different categories of sippc action labels. Example categories
of actions are no movement versus any-power-steering-movement; or no
movement versus a left-gesture-based-movement.
0: no robot action
1: power-steering: forward
2: power-steering: backward
3: power-steering: left
4: power-steering: right
5: gesture: forward
6: gesture: backward
7: gesture: left
8: gesture: right
"""
def get_action_onsets(actions, lower, upper):
    onsets = (actions[0:-1] == 0) & (actions[1:] >= lower) & (actions[1:] <=␣
 ↪upper)
    onsets = np.append(onsets, 0)
    return onsets


# Action all movement
label_motion = action > 0

# Action onsets of movements
label_onset_any = get_action_onsets(action, 1, 8) # any action
label_onset_ps = get_action_onsets(action, 1, 4) # power steering
label_onset_g = get_action_onsets(action, 5, 8) # gesture


# Compare the label categories
plt.figure(figsize=(FIGWIDTH*3,FIGHEIGHT))
```

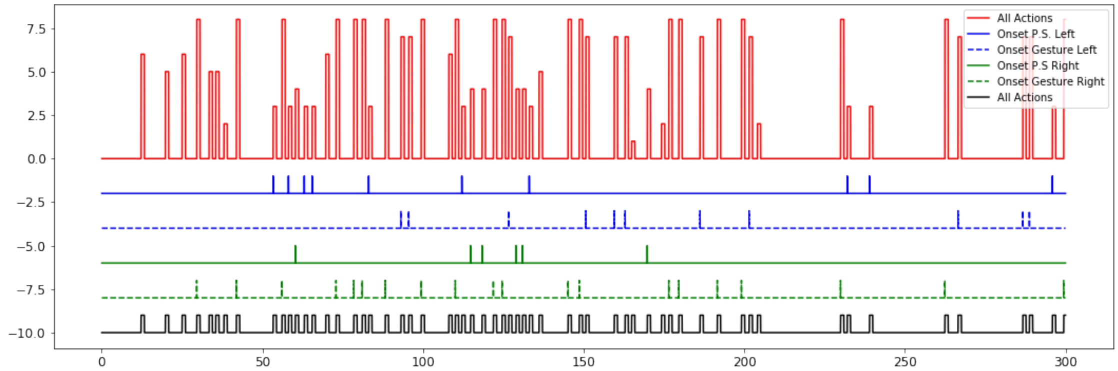
```
plt.plot(time, action, 'r', label='Actions')
plt.plot(time, label_onset_ps-1.1, 'b', label='Onset Power Steering')
plt.plot(time, label_onset_g-2.2, 'g', label='Onset Gesture')
#plt.plot(time, label_onset_any-3.3, 'k', label='Onset Any')
plt.plot(time, label_motion-3.3, 'k', label='Any Action')
plt.legend(loc='upper left')
```

[13]: <matplotlib.legend.Legend at 0x7f32c0332e10>



[14]:
```
""" PROVIDED
Extract left and right movement onsets from power steering and gesture actions
"""
label_onset_ps_l = get_action_onsets(action, 3, 3) # left power steering
label_onset_ps_r = get_action_onsets(action, 4, 4) # right power steering
label_onset_g_l = get_action_onsets(action, 7, 7) # left gesture
label_onset_g_r = get_action_onsets(action, 8, 8) # right gesture

# Any left action onset: Left power steering OR left gesture
label_onset_l = label_onset_ps_l | label_onset_g_l

# Any right action onset: Right power steering OR right gesture
label_onset_r = label_onset_ps_r | label_onset_g_r



# Compare the labels categories
plt.figure(figsize=(FIGWIDTH*3,FIGHEIGHT))
plt.plot(time, action, 'r', label='All Actions')
plt.plot(time, label_onset_ps_l-2, 'b', label='Onset P.S. Left')
plt.plot(time, label_onset_g_l-4, 'b--', label='Onset Gesture Left')
plt.plot(time, label_onset_ps_r-6, 'g', label='Onset P.S Right')
plt.plot(time, label_onset_g_r-8, 'g--', label='Onset Gesture Right')
plt.plot(time, label_motion-10, 'k', label='All Actions')
plt.legend()
```

[14]:
```
<matplotlib.legend.Legend at 0x7f32c02baf60>
```



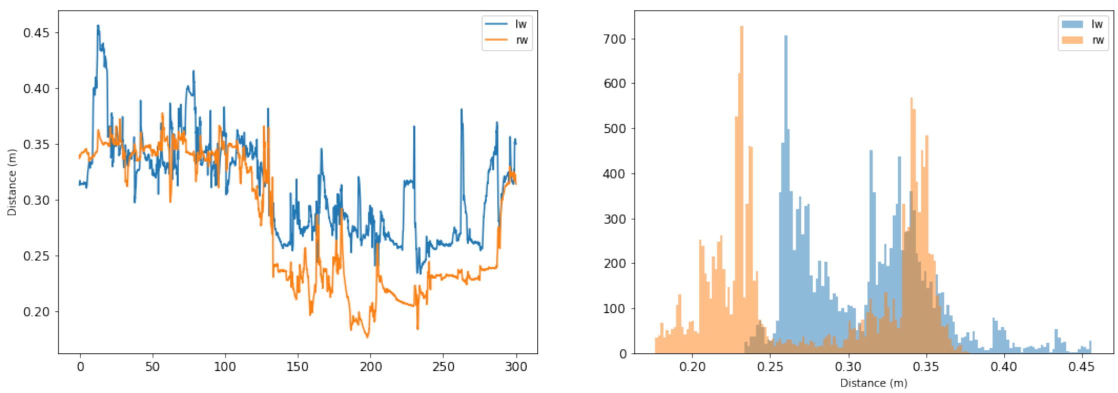
[15]:
```python
""" PROVIDED
"""
def compute_magnitude(mtx):
    '''
    Compute the magnitude as sqrt( sum_i(mtx[i]**2) )
    '''
    return np.sqrt((mtx * mtx).sum(axis=1))
```

EXTRACT AND CONSTRUCT DISTANCE LABELS

[16]:
```python
""" TODO
DISTANCE
Generate labels using the magnitude of the position (distance from the baby's
origin) for the left and right wrists.
Compute the magnitude of the left and right wrists' 3D-position-vector (e.g.
use the left_wrist_x, left_wrist_y, and left_wrist_z as a matrix to compute
the magnitude at each time point.)
Plot the magnitudes over time comparing left and right, and compare the␣
↪histograms
for the left and right magnitudes. These magnitudes are the distances of the
wrists from the baby's origin in 3D space. Not the best metric to determine␣
↪movement,
however, clear differences in the left and right distances can be observed.
"""

# Lists of position coordinate names
lw_pos_comp_names = ['left_wrist_x', 'left_wrist_y', 'left_wrist_z']
rw_pos_comp_names = ['right_wrist_x', 'right_wrist_y', 'right_wrist_z']

# Select the position coordinates
lw_pos = data_pos_vel[lw_pos_comp_names]
```

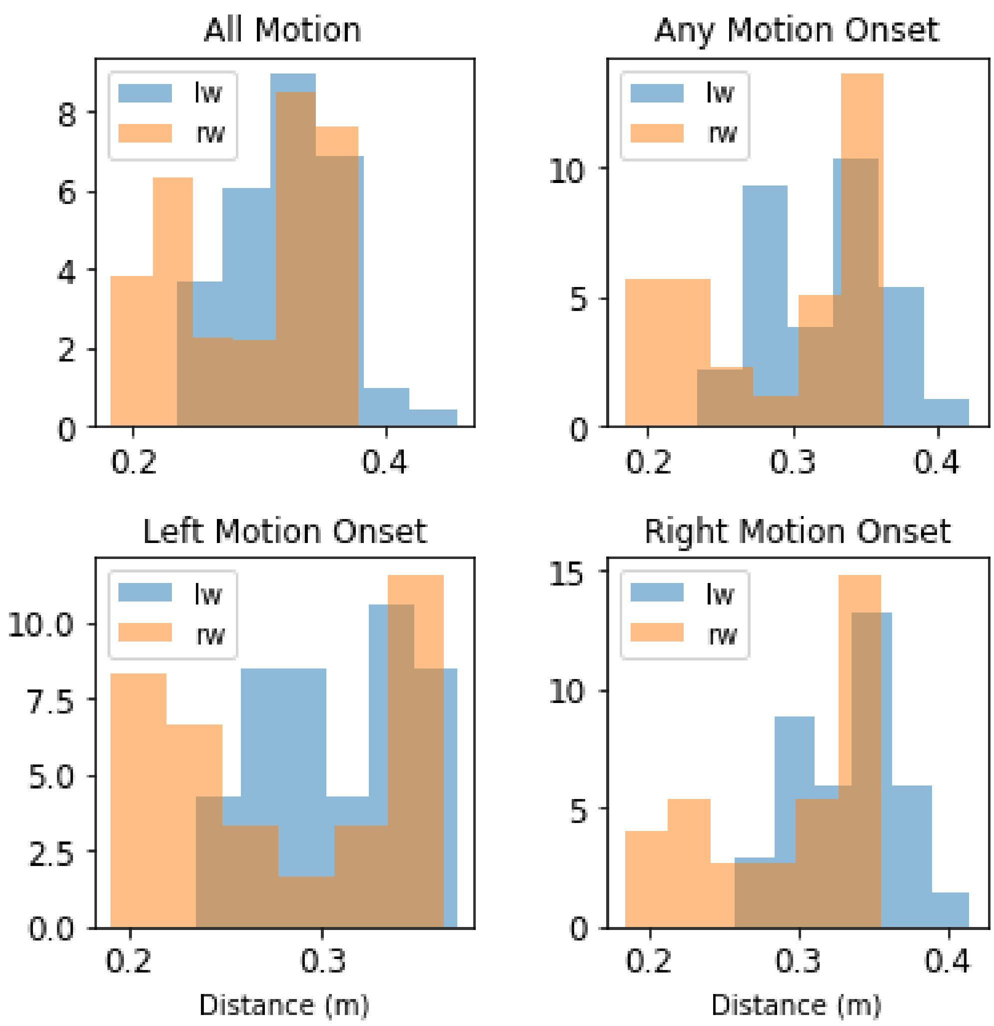
```
rw_pos = data_pos_vel[rw_pos_comp_names]

# TODO: compute the magnitude for the positions (i.e. the distances) for
#       the left and right wrists at every time point
lw_dist = ((lw_pos.values)**2).sum(axis=1)**0.5# TODO
rw_dist = ((rw_pos.values)**2).sum(axis=1)**0.5# TODO


# Number of bins for the histogram
nbins = int(np.sqrt(len(lw_dist)))

# PROVIDED: Compare the magnitudes for the left and right positions
# With labels and legends
plt.figure(figsize=(FIGWIDTH*3,FIGHEIGHT))
plt.subplot(1,2,1)
plt.plot(time, lw_dist, label='lw')
plt.plot(time, rw_dist, label='rw')
plt.ylabel('Distance (m)')
plt.legend()
plt.subplot(1,2,2)
plt.hist(lw_dist, bins=nbins, alpha=.5, label='lw')
plt.hist(rw_dist, bins=nbins, alpha=.5, label='rw')
plt.xlabel('Distance (m)')
plt.legend()
```

[16]: <matplotlib.legend.Legend at 0x7f32c0092588>



[17]:
```
""" PROVIDED
DISTANCE
Histograms of left vs right distances for various motion categories
"""
fig, axs = plt.subplots(2,2, figsize=(FIGWIDTH,FIGHEIGHT))
fig.subplots_adjust(wspace=.35, hspace=.35)
```

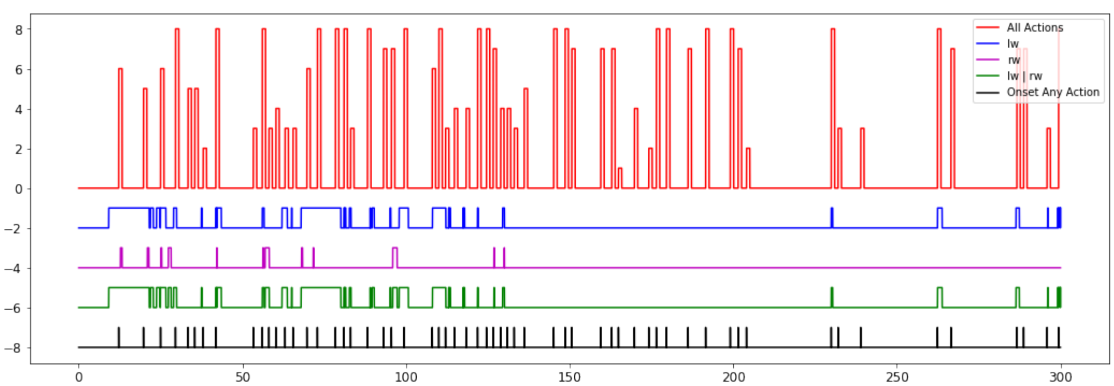
```
axs = axs.ravel()
label_sets = (label_motion, label_onset_any, label_onset_l, label_onset_r)
label_sets_names = ('All Motion', 'Any Motion Onset', 'Left Motion Onset',␣
↪'Right Motion Onset')
label_sets_zip = zip(label_sets, label_sets_names)
for i, (label_set, name) in enumerate(label_sets_zip):
    label_set = label_set.astype(bool).ravel()
    axs[i].hist(lw_dist[label_set], bins=6, density=True, alpha=.5, label='lw')
    axs[i].hist(rw_dist[label_set], bins=6, density=True, alpha=.5, label='rw')
    if i > 1: axs[i].set_xlabel('Distance (m)')
    axs[i].set_title(name)
    axs[i].legend()
```



[18]:
```
""" TODO
DISTANCE
```

```
Generate labels based on the magnitude of the position (distance) of the wrists.
Labels are set as whether the left wrist magnitude exceeds .35 OR the right
wrist exceeds .36
"""
# TODO: Extract the left wrist distance labels (i.e. 1 where ever the distance
#       of the left wrist exceeds .35). use lw_dist
lw_dist_lbls = lw_dist>.35# TODO

# TODO: Extract the right wrist distance labels (i.e. 1 where ever the distance
#       of the right wrist exceeds .36). use rw_dist
rw_dist_lbls = rw_dist>.36# TODO

# TODO: Construct labels 1 when either the left wrist distance exceeds .35 OR
#       the right wrist distance exceeds .36
dist_lbls = (lw_dist>.35) | (rw_dist>.36)# TODO



# PROVIDED: Compare the labels
plt.figure(figsize=(FIGWIDTH*3,FIGHEIGHT))
plt.plot(time, action, 'r', label='All Actions')
plt.plot(time, lw_dist_lbls-2, 'b', label='lw')
plt.plot(time, rw_dist_lbls-4, 'm', label='rw')
plt.plot(time, dist_lbls-6, 'g', label='lw | rw')
plt.plot(time, label_onset_any-8, 'k', label='Onset Any Action')
plt.legend()
```

[18]: <matplotlib.legend.Legend at 0x7f32c03ede80>

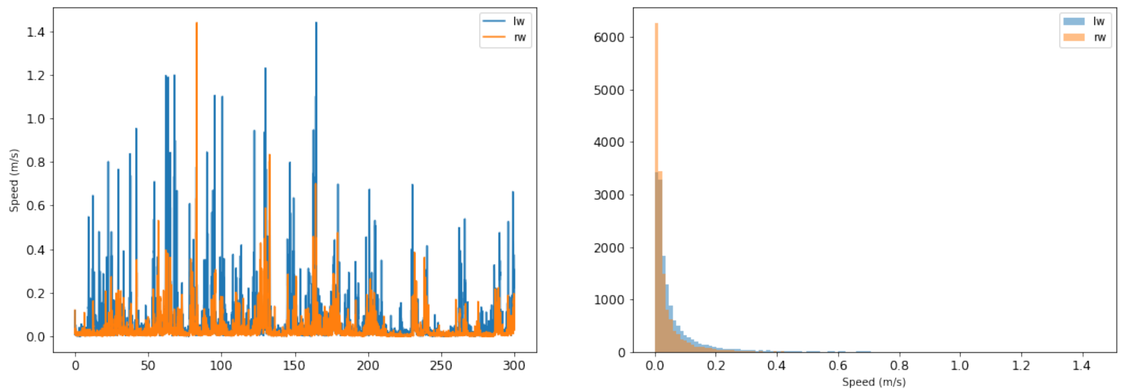


EXTRACT AND CONSTRUCT SPEED LABELS

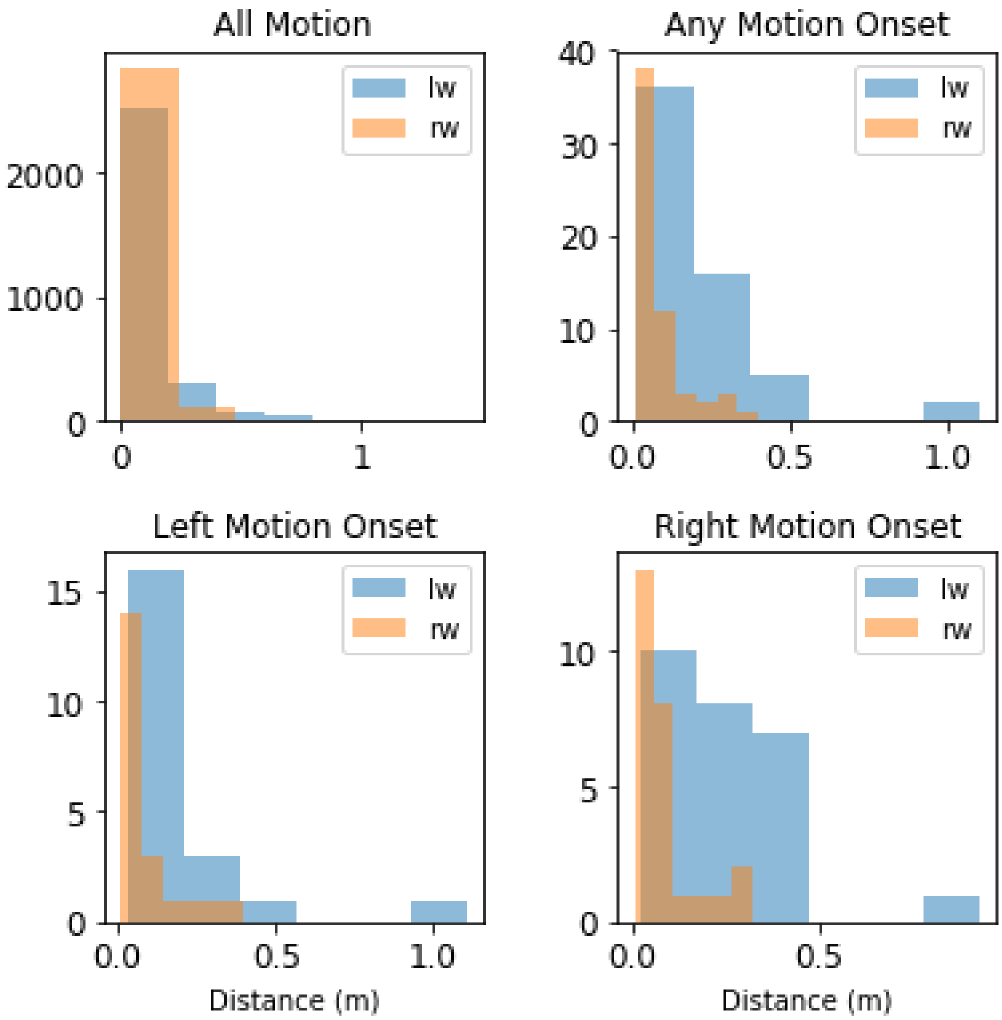
[19]:
```
""" TODO
SPEED
Compute the magnitude of the left and right wrists' 3D-velocity-vector (e.g.
```

```
use the d_left_wrist_x, d_left_wrist_y, and d_left_wrist_z as a matrix to␣
↪compute
the magnitude at each time point.)
Plot the magnitudes over time comparing left and right, and compare the␣
↪histograms
for the left and right magnitudes. These magnitudes are the speeds of the
baby's wrists.
Compute the magnitudes, plot the magnitudes over tme comparing left and right,
and compare the histograms for the left and right
"""
# Lists of velocity coordinate names
lw_vel_comp_names = ['d_left_wrist_x', 'd_left_wrist_y', 'd_left_wrist_z']
rw_vel_comp_names = ['d_right_wrist_x', 'd_right_wrist_y', 'd_right_wrist_z']

# Select the velocity coordinates
lw_vel = data_pos_vel[lw_vel_comp_names]
rw_vel = data_pos_vel[rw_vel_comp_names]

# TODO: compute the magnitude for the velocities (i.e. the speeds) at every␣
↪time point
lw_spd = compute_magnitude(lw_vel)# TODO
rw_spd = compute_magnitude(rw_vel)# TODO


# PROVIDED: Compare the magnitudes for the left and right velocites
# With labels and legends
plt.figure(figsize=(FIGWIDTH*3,FIGHEIGHT))
plt.subplot(1,2,1)
plt.plot(time, lw_spd, label='lw')
plt.plot(time, rw_spd, label='rw')
plt.ylabel("Speed (m/s)")
plt.legend()
plt.subplot(1,2,2)
plt.hist(lw_spd, bins=nbins, alpha=.5, label='lw')
plt.hist(rw_spd, bins=nbins, alpha=.5, label='rw')
plt.xlabel("Speed (m/s)")
plt.legend()
```

[19]: <matplotlib.legend.Legend at 0x7f32bd4d8eb8>



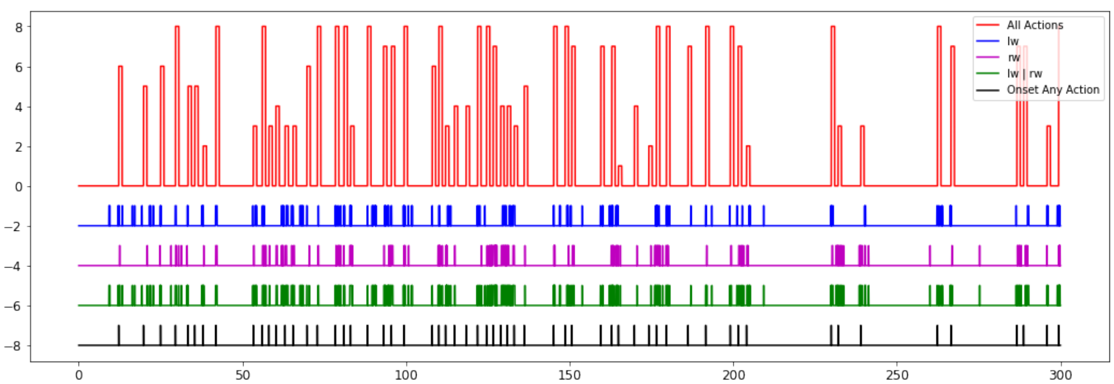
[20]:
```
""" PROVIDED
SPEED
Histograms of left vs right speeds for various motion categories
"""
fig, axs = plt.subplots(2,2, figsize=(FIGWIDTH,FIGHEIGHT))
fig.subplots_adjust(wspace=.35, hspace=.35)
axs = axs.ravel()
label_sets = (label_motion, label_onset_any, label_onset_l, label_onset_r)
label_sets_names = ('All Motion', 'Any Motion Onset', 'Left Motion Onset',␣
↪'Right Motion Onset')
label_sets_zip = zip(label_sets, label_sets_names)
for i, (label_set, name) in enumerate(label_sets_zip):
    label_set = label_set.astype(bool).ravel()
    axs[i].hist(lw_spd[label_set], bins=6, alpha=.5, label='lw')
    axs[i].hist(rw_spd[label_set], bins=6, alpha=.5, label='rw')
    if i > 1: axs[i].set_xlabel('Distance (m)')
    axs[i].set_title(name)
    axs[i].legend()
```



[21]:
```python
""" TODO
SPEED
Generate labels based on the speed of the wrists. Labels are set as whether
the left wrist speed exceeds .24 OR the right wrist speed exceeds .13.
"""
# TODO: Extract the left wrist speed labels (i.e. 1 where ever the speed of
#       the left wrist exceeds .24). use lw_spd
lw_spd_lbls = lw_spd>.24# TODO

# TODO: Extract the right wrist speed labels (i.e. 1 where ever the speed of
#       the right wrist exceeds .13). use lw_spd
rw_spd_lbls = rw_spd>.13# TODO

# TODO: Construct labels 1 when either the left wrist speed exceeds .24 OR
#       the right wrist speed exceeds .13
```

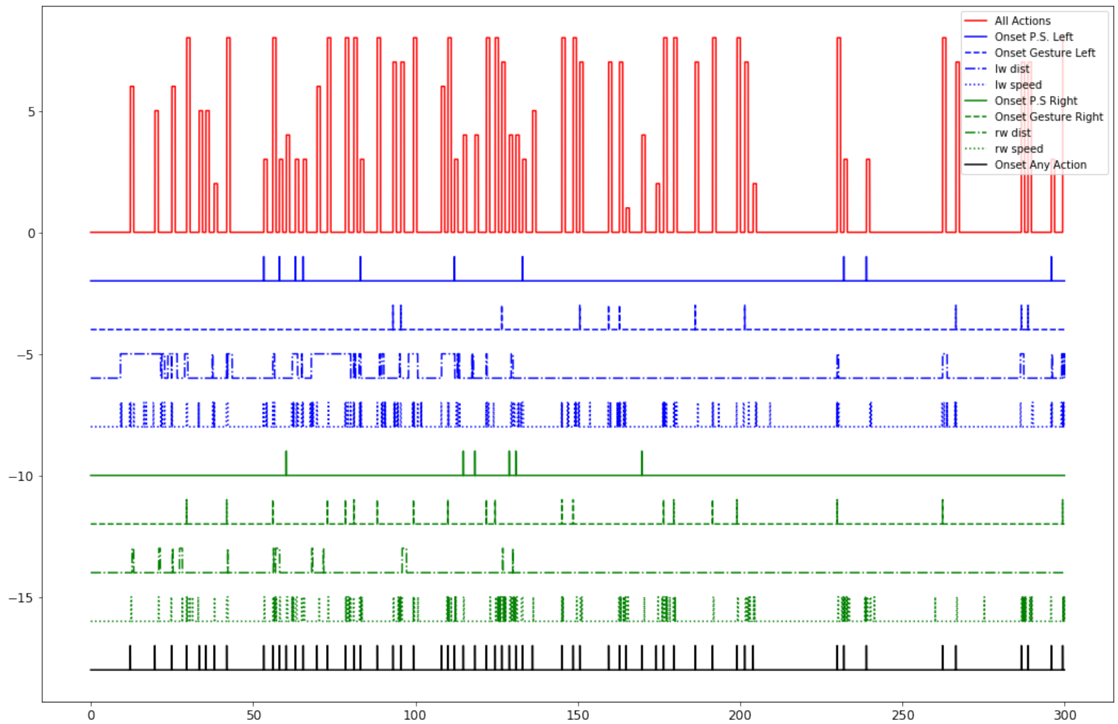
```
spd_lbls = (lw_spd>.24) | (rw_spd>.13)# TODO


# PROVIDED: Compare the labels
plt.figure(figsize=(FIGWIDTH*3,FIGHEIGHT))
plt.plot(time, action, 'r', label='All Actions')
plt.plot(time, lw_spd_lbls-2, 'b', label='lw')
plt.plot(time, rw_spd_lbls-4, 'm', label='rw')
plt.plot(time, spd_lbls-6, 'g', label='lw | rw')
plt.plot(time, label_onset_any-8, 'k', label='Onset Any Action')
plt.legend()
```

[21]: <matplotlib.legend.Legend at 0x7f32bd3a2320>



[22]:
```
""" PROVIDED
Plot all the label types for left and right
"""
plt.figure(figsize=(FIGWIDTH*3,FIGHEIGHT*2))
plt.plot(time, action, 'r', label='All Actions')
plt.plot(time, label_onset_ps_l-2, 'b', label='Onset P.S. Left')
plt.plot(time, label_onset_g_l-4, 'b--', label='Onset Gesture Left')
plt.plot(time, lw_dist_lbls-6, 'b-.', label='lw dist')
plt.plot(time, lw_spd_lbls-8, 'b:', label='lw speed')
plt.plot(time, label_onset_ps_r-10, 'g', label='Onset P.S Right')
plt.plot(time, label_onset_g_r-12, 'g--', label='Onset Gesture Right')
plt.plot(time, rw_dist_lbls-14, 'g-.', label='rw dist')
plt.plot(time, rw_spd_lbls-16, 'g:', label='rw speed')
plt.plot(time, label_onset_any-18, 'k', label='Onset Any Action')
plt.legend()
```

[22]: <matplotlib.legend.Legend at 0x7f32bd0f0e80>

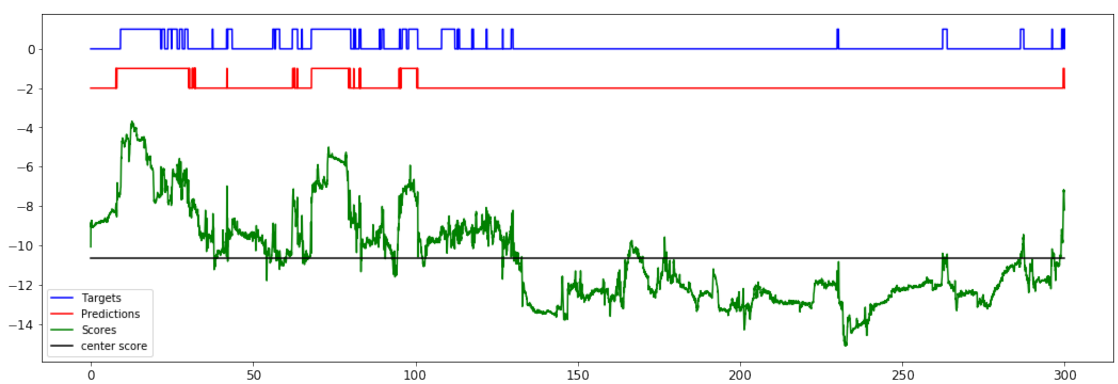


6 Classification Using Cross Validation

[23]:
```
""" TODO
DISTANCE
Create a SGDClassifier with random_state=42, max_iter=1e4, tol=1e-3, and
that uses a log loss function. Fit the model using the position x, y, z
and velocity x, y, z for all limbs as the input features to the model. Use
the distance labels as the output of the model.
Use cross_val_predict() to get predictions for each sample and their
cooresponding scores. Use 20 cross validation splits (i.e. cv=20).
Plot the true labels, predictions, and the scores.
For more information observe the general references above
"""
# Model input
X = inputs_pos_vel
# Model output
y = dist_lbls

# TODO: Create and fit the classifer
clf = SGDClassifier(loss= 'log', random_state=42, max_iter= 1e4, tol= 1e-3, )#␣
↪TODO
```

```
clf.fit(X, y)

# TODO: use cross_val_predict() to compute the scores by setting the method
#       parameter equal to 'decision_function'. Please see the reference links␣
↪above
dist_scores = cross_val_predict(clf, X, y, cv=20, method= 'decision_function')#␣
↪TODO

# TODO: use cross_val_predict() to compute the predicted labels by setting the␣
↪method
#       parameter equal to 'predict'. Please see the reference links above
dist_preds = cross_val_predict(clf, X, y, cv=20)# TODO


# PROVIDED: Compare the true labels to the predicted labels and the scores
mu_score = np.mean(dist_scores)

plt.figure(figsize=(FIGWIDTH*3,FIGHEIGHT))
plt.plot(time, dist_lbls, 'b', label='Targets')
plt.plot(time, dist_preds-2, 'r', label='Predictions')
plt.plot(time, dist_scores-8, 'g', label='Scores')
plt.plot([0, time.max()], [mu_score-8, mu_score-8],
         'k', label='center score')
plt.legend()
```

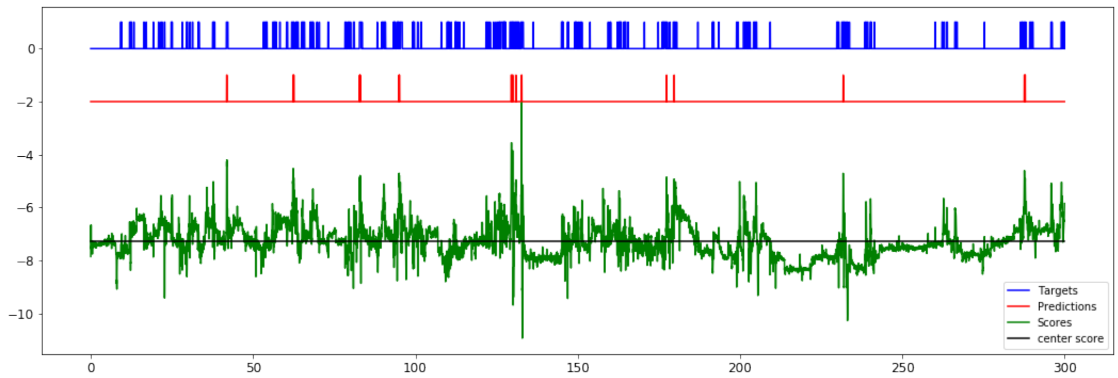
[23]: <matplotlib.legend.Legend at 0x7f32c04a7588>



[24]:
```
""" TODO
SPEED
Create a SGDClassifier with random_state=42, max_iter=10000, tol=1e-3, and
that uses a log loss function. Fit the model using the position x, y, z
and velocity x, y, z for all limbs as the input features to the model. Use
the speed labels as the output of the model.
```

```
Use cross_val_predict() to get predictions for each sample and their
cooresponding score. Use 20 cross validation splits. Predict the speed labels
Plot the true labels, predictions, and the scores
"""
# Model output
y = spd_lbls

# TODO: Create and fit the classifer
clf = SGDClassifier(loss= 'log', random_state=42, max_iter= 1e4, tol= 1e-3, )#␣
↪TODO
# TODO: fit the classifier

# TODO: use cross_val_predict() to compute the scores by setting the method
#       parameter equal to 'decision_function'. Please see the reference links␣
↪above
spd_scores = cross_val_predict(clf, X, y, cv=20, method= 'decision_function')#␣
↪TODO

# TODO: use cross_val_predict() to compute the predicted labels by setting the␣
↪method
#       parameter equal to 'predict'. Please see the reference links above
spd_preds = cross_val_predict(clf, X, y, cv=20, method= 'predict')# TODO


# PROVIDED: Compare the true labels to the predicted labels and the scores
mu_score = np.mean(spd_scores)

plt.figure(figsize=(FIGWIDTH*3,FIGHEIGHT))
plt.plot(time, spd_lbls, 'b', label='Targets')
plt.plot(time, spd_preds-2, 'r', label='Predictions')
plt.plot(time, spd_scores-5, 'g', label='Scores')
plt.plot([0, time.max()], [mu_score-5, mu_score-5],
         'k', label='center score')
plt.legend()
```

[24]:
```
<matplotlib.legend.Legend at 0x7f32c0420748>
```



7 Plotting Functions - Performance Results

- Confusion Matrix Color Map
- K.S. Plot
- ROC Curve Plot

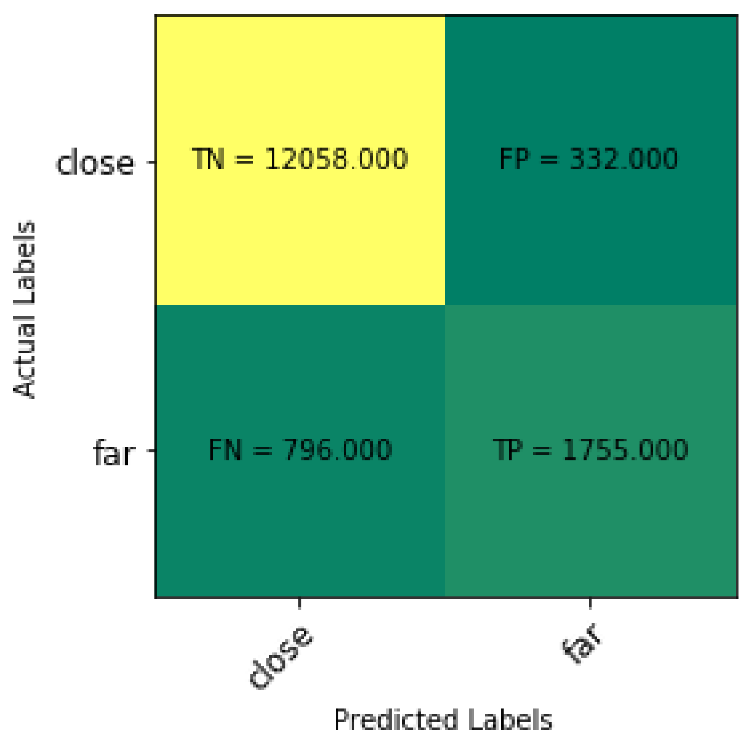
[25]:
```
""" PROVIDED
"""
# Generate a color map plot for a confusion matrix
def confusion_mtx_colormap(mtx, xnames, ynames, cbarlabel=""):
    '''
    Generate a figure that plots a colormap of a matrix
    PARAMS:
        mtx: matrix of values
        xnames: list of x tick names
        yname: list of the y tick names
    '''
    nxvars = mtx.shape[1]
    nyvars = mtx.shape[0]

    # create the figure and plot the correlation matrix
    fig, ax = plt.subplots()
    im = ax.imshow(mtx, cmap='summer')
    if not cbarlabel == "":
        cbar = ax.figure.colorbar(im, ax=ax)
        cbar.ax.set_ylabel(cbarlabel, rotation=-90, va="bottom")

    # Specify the row and column ticks and labels for the figure
    ax.set_xticks(range(nxvars))
    ax.set_yticks(range(nyvars))
    ax.set_xticklabels(xnames)
    ax.set_yticklabels(ynames)
```

```python
    ax.set_xlabel("Predicted Labels")
    ax.set_ylabel("Actual Labels")

    # Rotate the tick labels and set their alignment.
    plt.setp(ax.get_xticklabels(), rotation=45,
             ha="right", rotation_mode="anchor")

    # Loop over data dimensions and create text annotations.
    lbl = np.array([['TN', 'FP'], ['FN', 'TP']])
    for i in range(nyvars):
        for j in range(nxvars):
            text = ax.text(j, i, "%s = %.3f" % (lbl[i,j], mtx[i, j]),
                           ha="center", va="center", color="k")
            #text.set_path_effects([peffects.withStroke(linewidth=2,␣
 ↪foreground='w')])

    return fig, ax

# Compute the ROC Curve and generate the KS plot
def ks_roc_plot(targets, scores, FIGWIDTH=12, FIGHEIGHT=6, FONTSIZE=16):
    '''
    Generate a figure that plots a colormap of a matrix
    PARAMS:
        mtx: matrix of values
        xnames: list of x tick names
        yname: list of the y tick names
    '''
    fpr, tpr, thresholds = roc_curve(targets, scores)
    auc_res = auc(fpr, tpr)

    # Generate KS plot
    fig, ax = plt.subplots(1, 2, figsize=(FIGWIDTH,FIGHEIGHT))
    axs = ax.ravel()
    ax[0].plot(thresholds, tpr, color='b')
    ax[0].plot(thresholds, fpr, color='r')
    ax[0].plot(thresholds, tpr - fpr, color='g')
    ax[0].invert_xaxis()
    ax[0].set_xlabel('threshold', fontsize=FONTSIZE)
    ax[0].set_ylabel('fraction', fontsize=FONTSIZE)
    ax[0].legend(['TPR', 'FPR', 'K-S Distance'], fontsize=FONTSIZE)

    # Generate ROC Curve plot
    ax[1].plot(fpr, tpr, color='b')
    ax[1].plot([0,1], [0,1], 'r--')
    ax[1].set_xlabel('FPR', fontsize=FONTSIZE)
    ax[1].set_ylabel('TPR', fontsize=FONTSIZE)
    ax[1].set_aspect('equal', 'box')
```

```
    auc_text = ax[1].text(.05, .95, "AUC = %.4f" % auc_res,
                          color="k", fontsize=FONTSIZE)
    print("AUC:", auc_res)

    return fpr, tpr, thresholds, auc, fig, axs
```

[26]:
```
""" TODO
DISTANCE
Compute the confusion matrix using sklearn's confusion_matrix() function and
generate a color map using the provided confusion_mtx_colormap() for the model
built using the distance labels.
"""
label_names = ['close', 'far']

dist_confusion_mtx = confusion_matrix(dist_lbls, dist_preds)# TODO

# TODO: generate the confusion matrix color map
fig, ax= confusion_mtx_colormap(dist_confusion_mtx, label_names, label_names)


nneg = dist_confusion_mtx[0].sum()
npos = dist_confusion_mtx[1].sum()
npos, nneg
```

[26]: (2551, 12390)

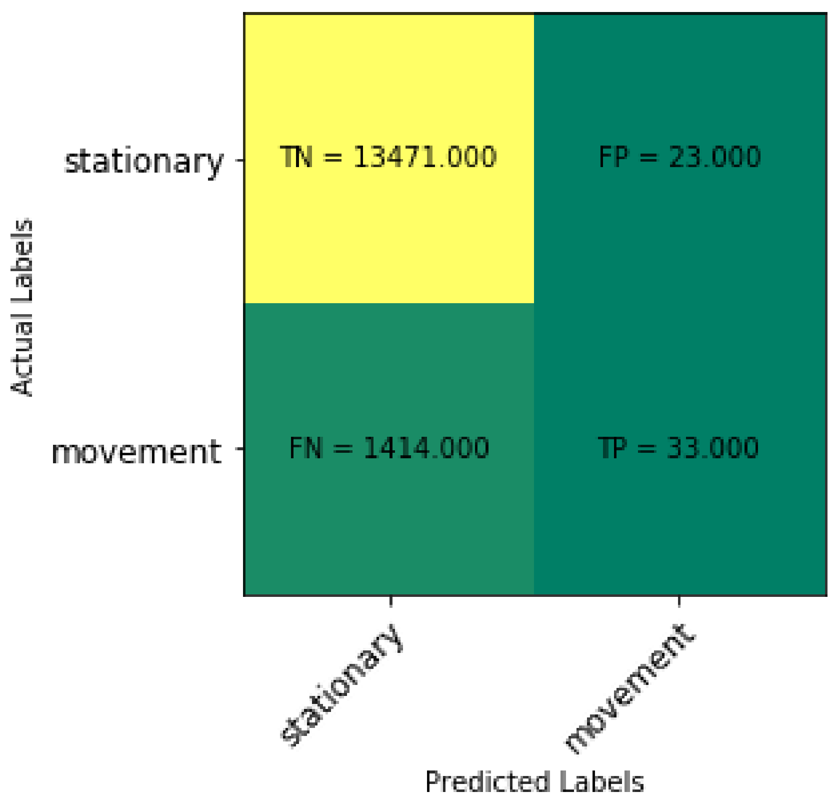


[27]:

```
""" TODO
SPEED
Compute the confusion matrix using sklearn's confusion_matrix() function and
generate a color map using the provided confusion_mtx_colormap() for the model
built using the speed labels.
"""
label_names = ['stationary', 'movement']

spd_confusion_mtx = confusion_matrix(spd_lbls, spd_preds)# TODO

# TODO: generate the confusion matrix color map
confusion_mtx_colormap(spd_confusion_mtx, label_names, label_names)

nneg = spd_confusion_mtx[0].sum()
npos = spd_confusion_mtx[1].sum()
npos, nneg
```

[27]:

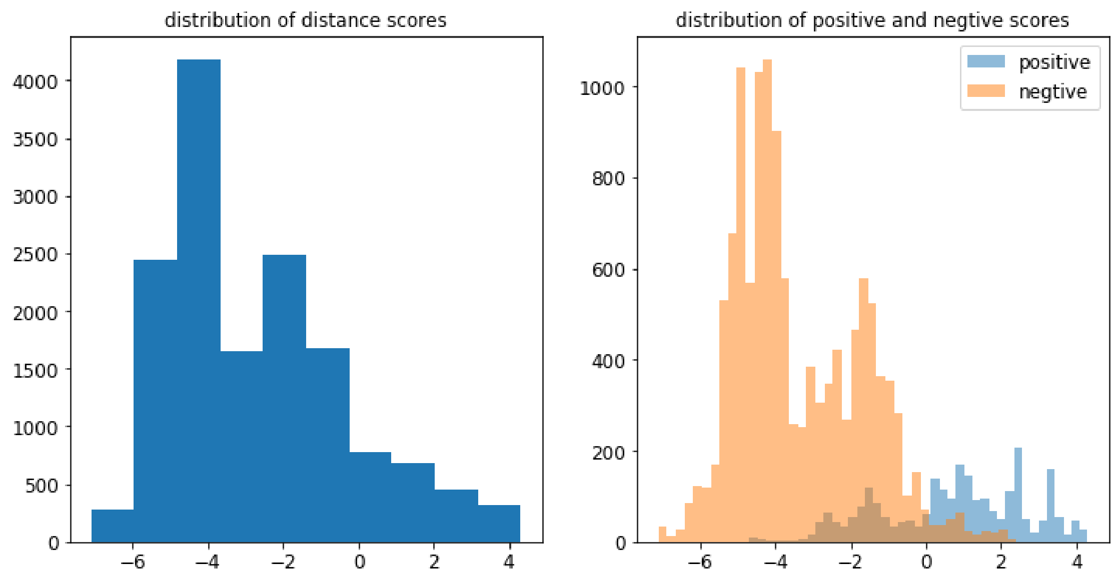
```
(1447, 13494)
```



[28]:

```
""" TODO
DISTANCE
Plot histograms of the scores from the model built using the distance labels.
Comparing distribution of scores for positive ang negative examples.
Create one subplot of the distribution of all the scores.
Create a second subplot overlaying the distribution of the scores of the␣
↪positive
examples (i.e. positive here means examples with a label of 1) with the␣
↪distribution
of the negative examples (i.e. positive here means examples with a label of 0).
Use 41 as the number of bins.
See the lecture on classifiers for examples
"""
scores_pos= [dist_scores[i] for (i ,b) in enumerate(dist_lbls) if b>0 ]
scores_neg= [dist_scores[i] for (i ,b) in enumerate(dist_lbls) if b==0]


fig, ax= plt.subplots(1,2,figsize=(FIGWIDTH*2, FIGHEIGHT))
ax[0].hist(dist_scores)
ax[0].set_title('distribution of distance scores', fontsize= FONTSIZE)
ax[1].hist(scores_pos, bins= 41, alpha= .5, label= 'positive')
ax[1].hist(scores_neg, bins= 41, alpha= .5, label= 'negtive')
ax[1].set_title('distribution of positive and negtive scores',␣
↪fontsize=FONTSIZE)
plt.legend(loc= 'upper right', fontsize= FONTSIZE)
```

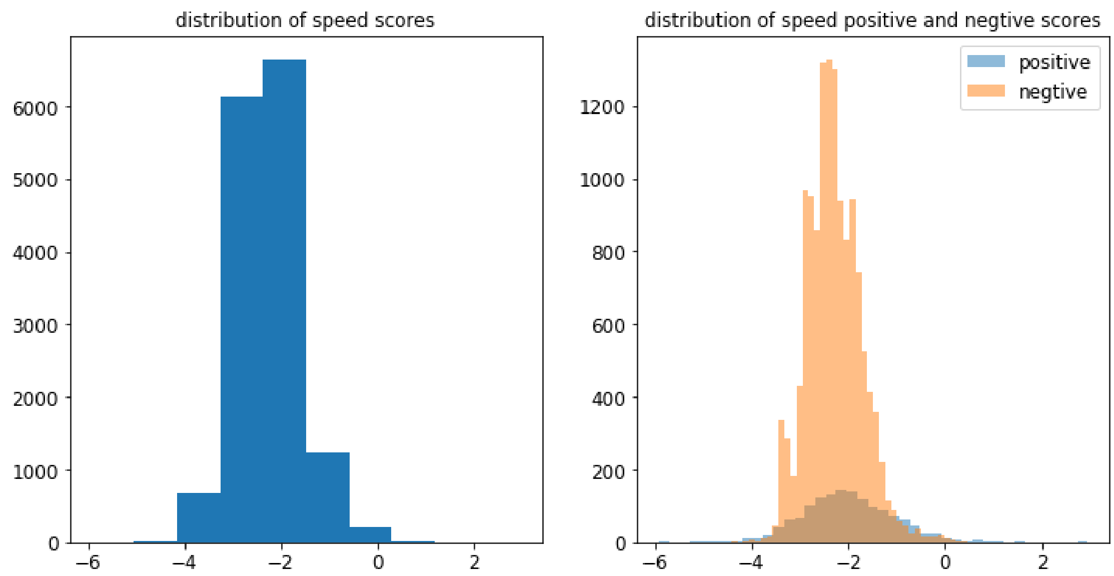
[28]: <matplotlib.legend.Legend at 0x7f32bcf55cc0>



[29]:

```
""" TODO
SPEED
Plot histograms of the scores from the model built using the speed labels.
Comparing distribution of scores for positive ang negative examples.
Create one subplot of the distribution of all the scores.
Create a second subplot overlaying the distribution of the scores of the␣
↪positive
examples (i.e. positive here means examples with a label of 1) with the␣
↪distribution
of the negative examples (i.e. positive here means examples with a label of 0).
Use 41 as the number of bins.
See the lecture on classifiers for examples
"""

scores_pos= [spd_scores[i] for (i ,b) in enumerate(spd_lbls) if b>0 ]
scores_neg= [spd_scores[i] for (i ,b) in enumerate(spd_lbls) if b==0]


fig, ax= plt.subplots(1,2,figsize=(FIGWIDTH*2, FIGHEIGHT))
ax[0].hist(spd_scores)
ax[0].set_title('distribution of speed scores', fontsize= FONTSIZE)
ax[1].hist(scores_pos, bins= 41, alpha= .5, label= 'positive')
ax[1].hist(scores_neg, bins= 41, alpha= .5, label= 'negtive')
ax[1].set_title('distribution of speed positive and negtive scores',␣
↪fontsize=FONTSIZE)
plt.legend(loc= 'upper right', fontsize= FONTSIZE)
```

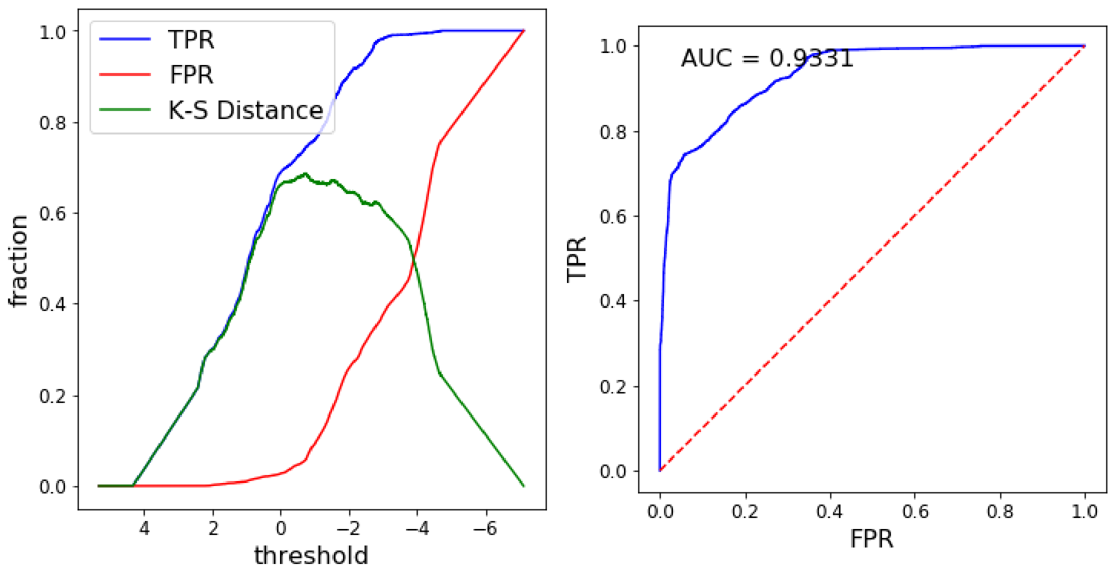
[29]: <matplotlib.legend.Legend at 0x7f32bcdc5d68>



[30]:
```python
""" TODO
DISTANCE
Use ks_roc_plot() to plot the ROC curve and the KS plot for the model
constructed with the distance labels
"""
fpr, tpr, thresholds, auc, fig, axs= ks_roc_plot(dist_lbls, dist_scores)
axs[0].set_title('')
```

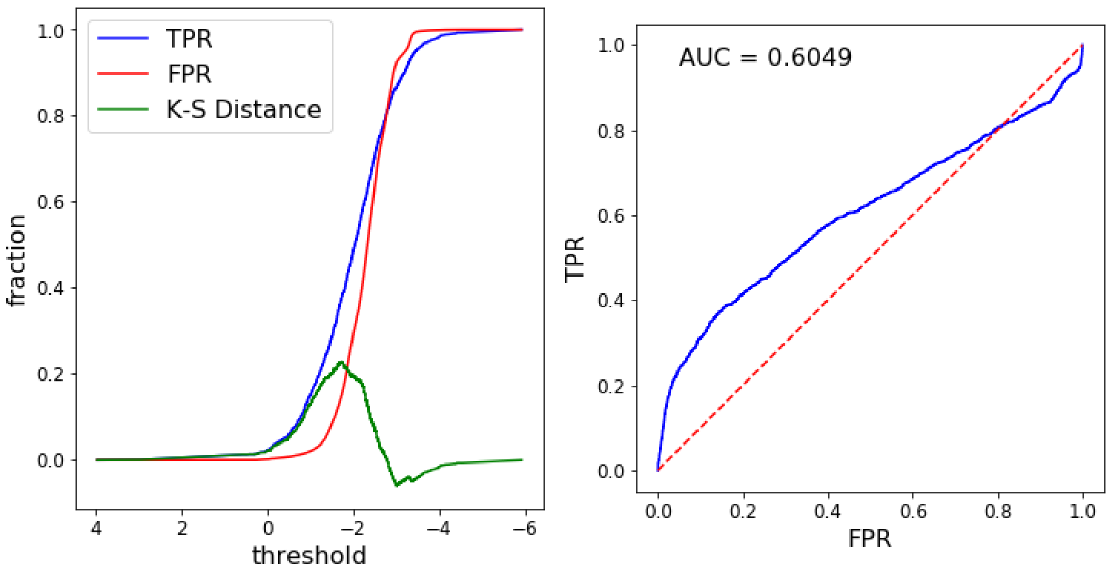
```
AUC: 0.9330701945050588
```

[30]:
```
Text(0.5, 1.0, '')
```



[31]:
```python
""" TODO
SPEED
Use ks_roc_plot() to plot the ROC curve and the KS plot for the model
constructed with the speed labels
"""

fpr, tpr, thresholds, auc, fig, axs= ks_roc_plot(spd_lbls, spd_scores)
```

```
AUC: 0.6049139144900357
```


TPR
FPR
K-S Distance
fraction
threshold
AUC = 0.6049
TPR
FPR