homework3-skel

September 29, 2020

NAME: Nigel Mansell
SECTION #: CS-5970-995

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 missing data (flagged as NaNs).

This assignment utilizes code examples from the lecture on classifiers

- Pipelines
- Classification
  - Label extraction and construction
  - Prediction
  - Performance Evaluation
  - Utilization of Built-In Cross Validation Tools

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

1.0.3 Hand-In Procedure

- Execute all cells so they are showing correct results
- Notebook:

    – Submit this file (.ipynb) to the Canvas HW3 dropbox
- PDF:
    – File/Print/Print to file -> Produces a copy of the notebook in PDF format
    – Submit the PDF file to the Gradescope HW3 dropbox

[153]:
```
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

[154]:
```
""" 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.
"""
# may need to adjust the filepath if you are not working on Oscer
fname = '~/Desktop//mlp/mlp_2020/datasets/baby1/subject_k2_w05.csv'

#creating dataframe from file and output the info
baby_data_raw = pd.read_csv(fname)
```

```
baby_data_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15000 entries, 0 to 14999
Data columns (total 43 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   time              15000 non-null  float64
 1   left_wrist_x      14987 non-null  float64
 2   left_wrist_y      14987 non-null  float64
 3   left_wrist_z      14987 non-null  float64
 4   right_wrist_x     14984 non-null  float64
 5   right_wrist_y     14984 non-null  float64
 6   right_wrist_z     14984 non-null  float64
 7   left_elbow_x      15000 non-null  float64
 8   left_elbow_y      15000 non-null  float64
 9   left_elbow_z      15000 non-null  float64
 10  right_elbow_x     15000 non-null  float64
 11  right_elbow_y     15000 non-null  float64
 12  right_elbow_z     15000 non-null  float64
 13  left_shoulder_x   15000 non-null  float64
 14  left_shoulder_y   15000 non-null  float64
 15  left_shoulder_z   15000 non-null  float64
 16  right_shoulder_x  15000 non-null  float64
 17  right_shoulder_y  15000 non-null  float64
 18  right_shoulder_z  15000 non-null  float64
 19  left_knee_x       15000 non-null  float64
 20  left_knee_y       15000 non-null  float64
 21  left_knee_z       15000 non-null  float64
 22  right_knee_x      15000 non-null  float64
 23  right_knee_y      15000 non-null  float64
 24  right_knee_z      15000 non-null  float64
 25  left_ankle_x      15000 non-null  float64
 26  left_ankle_y      15000 non-null  float64
 27  left_ankle_z      15000 non-null  float64
 28  right_ankle_x     15000 non-null  float64
 29  right_ankle_y     15000 non-null  float64
 30  right_ankle_z     15000 non-null  float64
 31  left_foot_x       15000 non-null  float64
 32  left_foot_y       15000 non-null  float64
 33  left_foot_z       15000 non-null  float64
 34  right_foot_x      15000 non-null  float64
 35  right_foot_y      15000 non-null  float64
 36  right_foot_z      15000 non-null  float64
 37  upper_back_x      15000 non-null  float64
 38  upper_back_y      15000 non-null  float64
 39  upper_back_z      15000 non-null  float64
```

```
 40   sippc_action      15000 non-null  float64
 41   robot_vel_l       15000 non-null  float64
 42   robot_vel_r       15000 non-null  float64
dtypes: float64(43)
memory usage: 4.9 MB
```

[155]:

```python
""" TODO
Display the first few examples
"""

#displaying the head
display(baby_data_raw.head())
```

```
   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]
```

[156]:

```python
""" TODO
Display the last few examples
"""
```

```
#displaying the tail
display(baby_data_raw.tail())
```

```
         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]
```

[157]:
```
""" TODO
Display the summary statistics
"""

#calling describe to get summary statistics
baby_data_raw.describe()
```

[157]:

	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]
```

[158]:

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

#checking for nan values
baby_data_raw.isna().any()
```

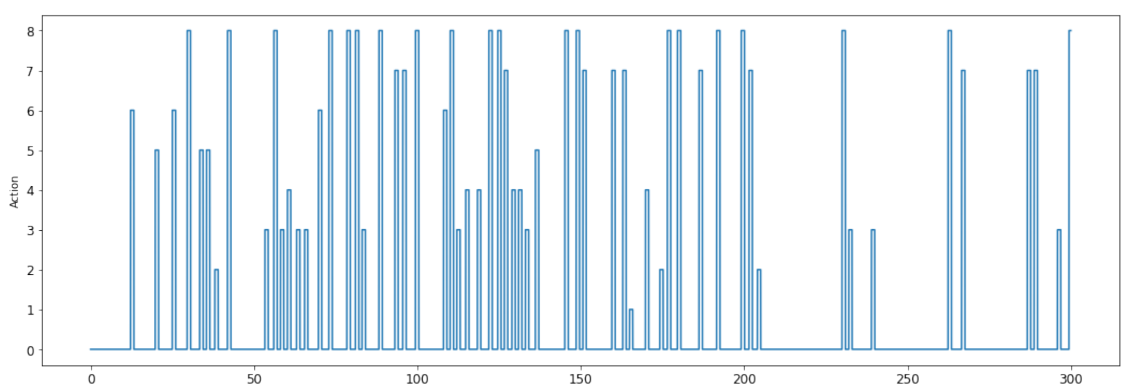
[158]:

```
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
```

[159]:
```
""" TODO
Plot the sippc actions over time for the original dataset.  These actions are␣
 ↪short
movements produced by the robot to aid the infant in locomoting in some␣
 ↪direction
(forward or left/right turn)
"""

#setting time and action
time = baby_data_raw['time']
action = baby_data_raw['sippc_action']

# TODO: Plot
plt.figure(figsize=(FIGWIDTH*3, FIGHEIGHT))
# TODO: complete this plot of time vs action

#ploting using time and action
plt.plot(time, action)
plt.xlabel("Time (s)")
plt.ylabel("Action")
```

[159]:
```
Text(0, 0.5, 'Action')
```



3 Data Selection

[160]:
```
""" 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
```

[161]:
```
""" 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

[162]:
```python
""" 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

[163]:
```
""" 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.
"""
# 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

[164]:
```
""" 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 an initial cleaning of the data
#using fit and transform
baby_data_prcd = pipe0.fit_transform(baby_data_raw)

# TODO: Use the result from the first pipeline to get the kinematic and
```

```
#       velocity features by using the pipe_kin_vel pipeline

#used baby data prcd for pipe
data_pos_vel = pipe_kin_vel.transform(baby_data_prcd)

# TODO: Use the result from the first pipeline to get the time by using
#       the pipe_time pipeline

#used baby data prcd for pipe
data_time = pipe_time.transform(baby_data_prcd)

# TODO: Use the result from the first pipeline to get the action by using
#       the pipe_action pipeline

#used baby data prcd for pipe
data_action = pipe_action.transform(baby_data_prcd)


# 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
```

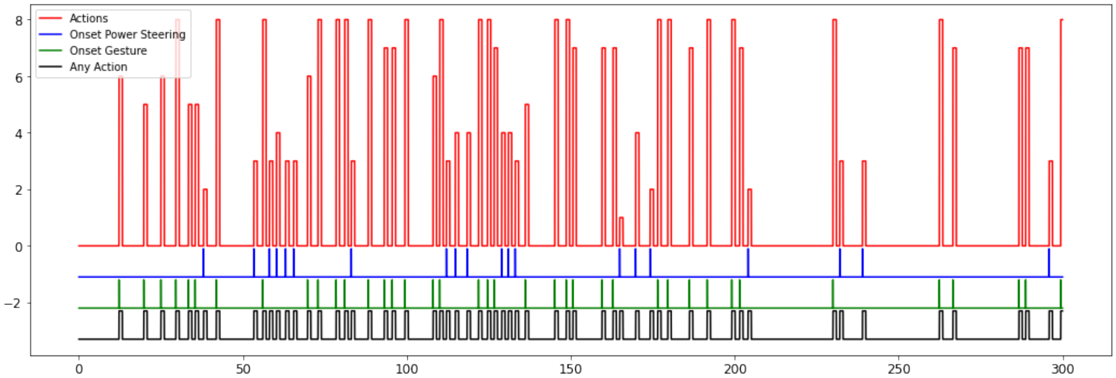
[164]: 14941

5.2 Observing and Obtaining Labels

[165]:
```
''' 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

This function finds all examples where the described action range is just␣
↪beginning to occur in the next example.
```

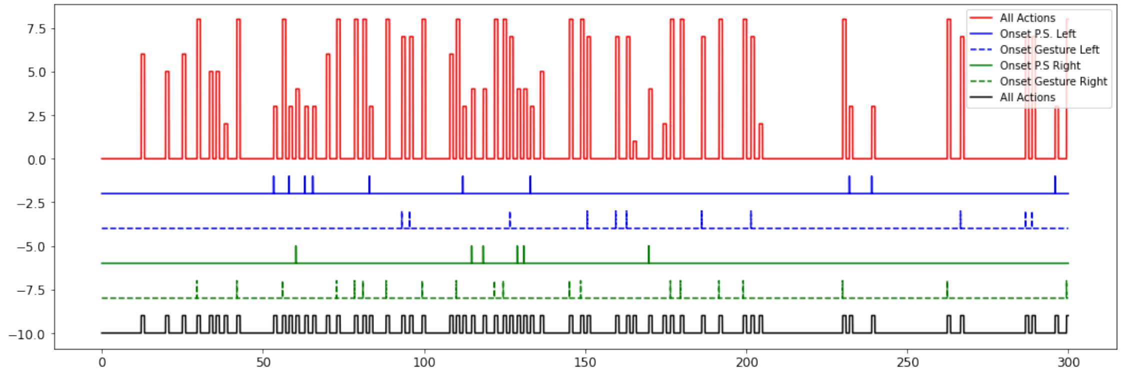
```
For example, if the actions np array is [[0],[3],[0],[1],[1],[1],[0],[2]] and␣
↪lower = 1 and upper = 2, the function
would return [[0],[0],[1],[0],[0],[0],[1],[0]]

actions[0:-1] is the array of actions for time steps 0, 1, ... N-2 (where N is␣
↪the length of the array)
action[1:] is the array of actions    for time steps 1, 2. ... N-1

'''
def get_action_onsets(actions, lower, upper):
    # Current element is zero; the next element is between lower and upper.
    #  The Boolean operators are done element-by-element
    onsets = (actions[0:-1] == 0) & (actions[1:] >= lower) & (actions[1:] <=␣
↪upper)
    # Append a zero to keep the lengths the same
    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')
```

[165]: <matplotlib.legend.Legend at 0x7fb6e6522af0>



[166]:
```
""" 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()
```

[166]: <matplotlib.legend.Legend at 0x7fb6e6482d00>



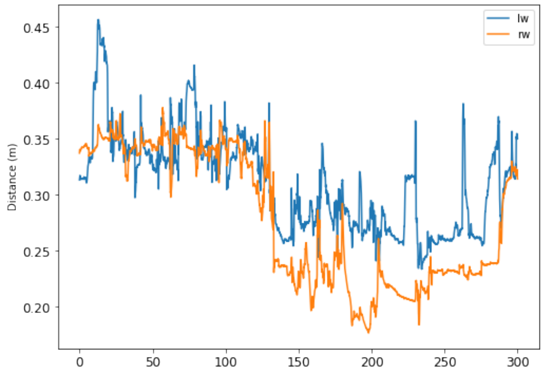
[167]:
```
""" PROVIDED
"""
def compute_magnitude(mtx):
    '''
    Compute the magnitude as sqrt( sum_i(mtx[i]**2) )
    '''
    return np.sqrt((mtx * mtx).sum(axis=1))
```

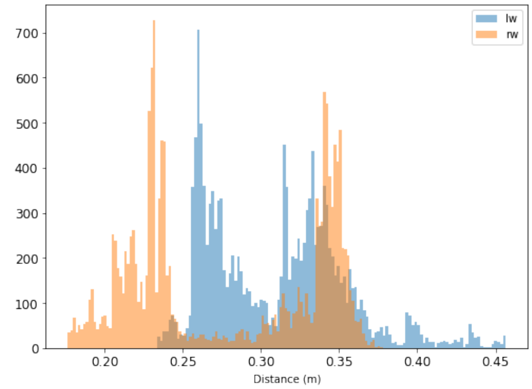
EXTRACT AND CONSTRUCT DISTANCE LABELS

[168]:
```
""" 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. This is 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 using the provided␣
↪function

#calling magnitude function
lw_dist = compute_magnitude(lw_pos)
rw_dist = compute_magnitude(rw_pos)


# 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()
```

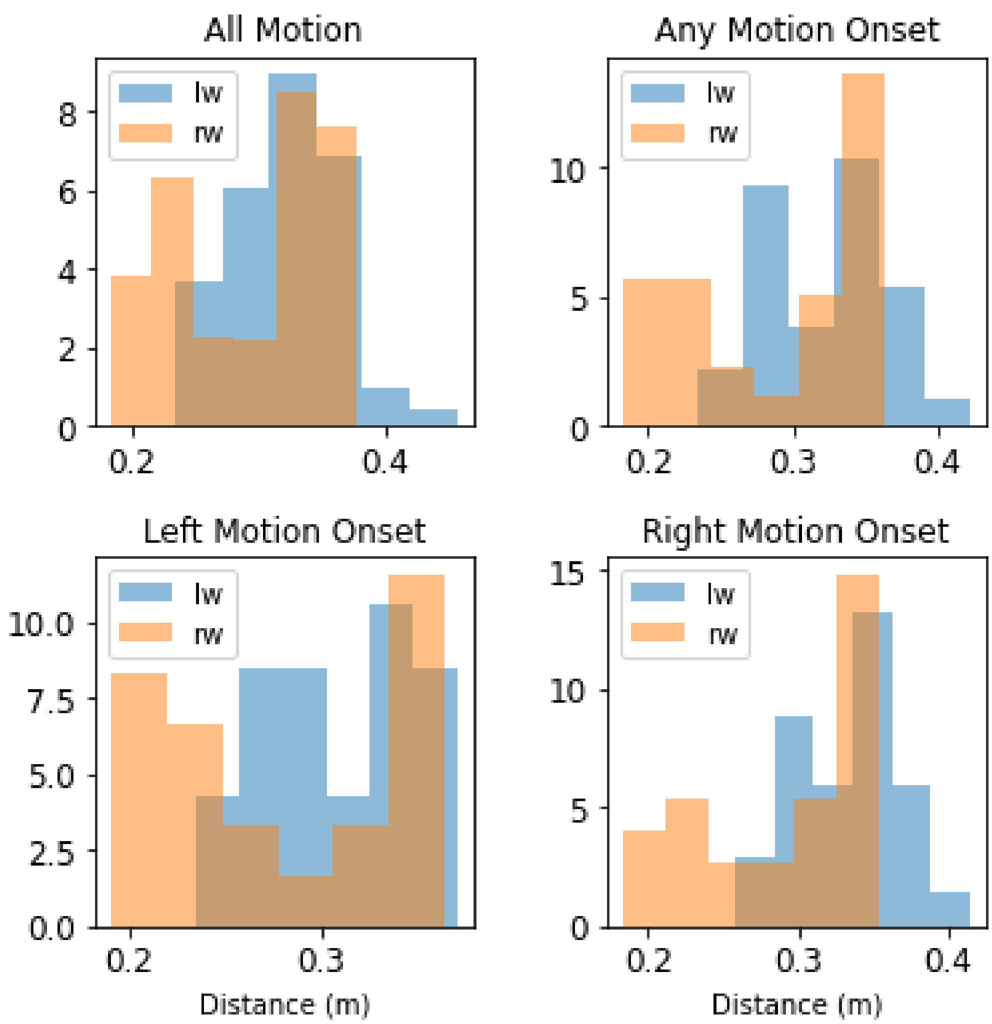
[168]: <matplotlib.legend.Legend at 0x7fb6e6425b80>





[169]:
```
""" 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)
```

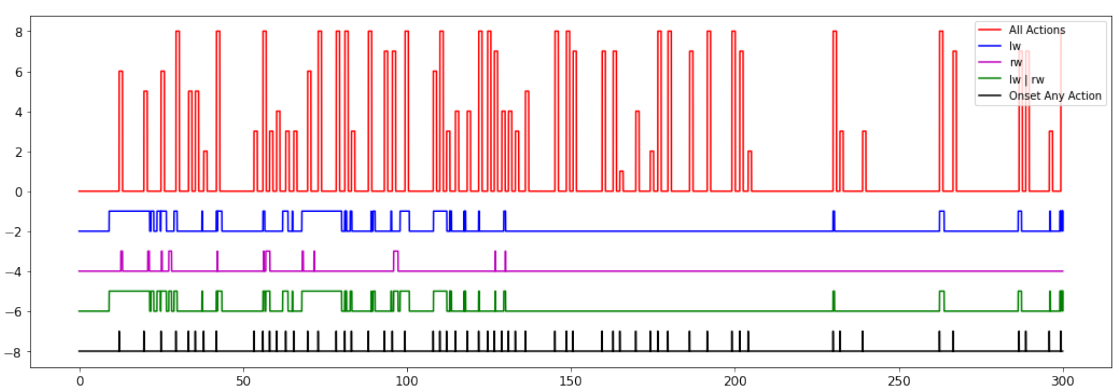
```python
axs = axs.ravel()
label_sets = (label_motion, label_onset_any, label_onset_l, label_onset_r)
label_sets_names = ('All Motion', 'Any Motion Onset', 'Left Motion Onset',
    'Right Motion Onset')
label_sets_zip = zip(label_sets, label_sets_names)
for i, (label_set, name) in enumerate(label_sets_zip):
    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()
```



[170]:
```python
""" 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

#using list comprehension to fill with 0s and 1s
lw_dist_lbls = np.array([1 if i > .35 else 0 for i in lw_dist])

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

#using list comprehension to fill with 0s and 1s
rw_dist_lbls = np.array([1 if i > .36 else 0 for i in rw_dist])


# TODO: Construct labels 1 when either the left wrist distance exceeds .35 OR
#       the right wrist distance exceeds .36

#using list comprehension with zip to fill with 0s and 1s
dist_lbls = np.array([1 if i > .35 or j > .36 else 0 for i, j in zip(lw_dist,␣
 ↪rw_dist)])

# 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()
```

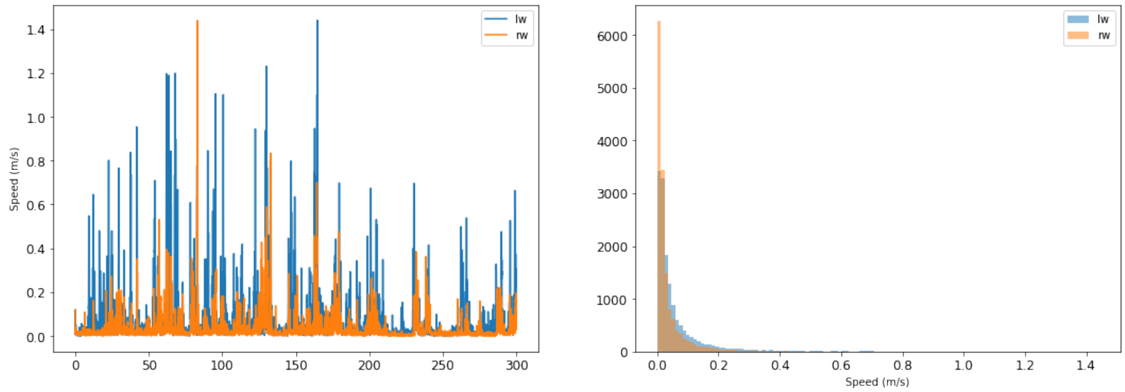
```
[170]: <matplotlib.legend.Legend at 0x7fb6e5f71fd0>
```



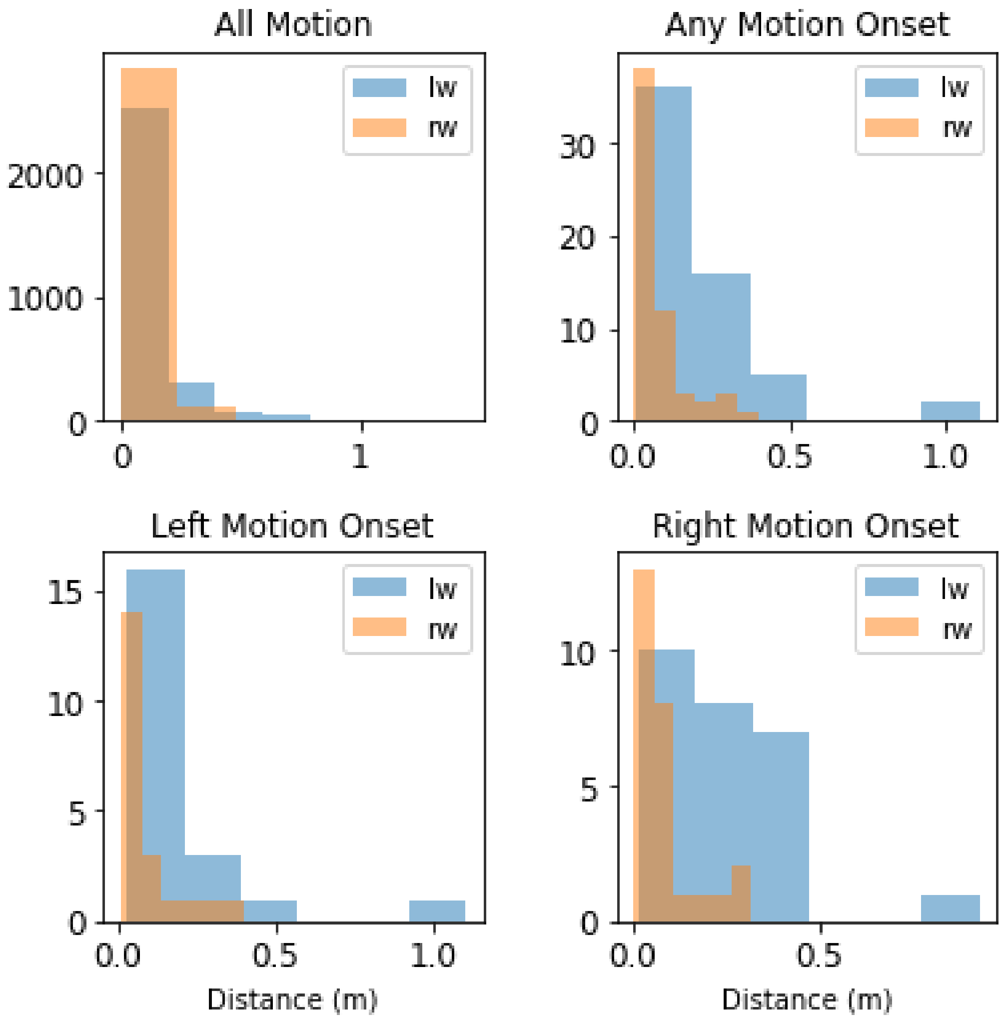
EXTRACT AND CONSTRUCT SPEED LABELS

[171]:
```
""" 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 time 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
#       using the provided function

#calling magnitude function
lw_spd = compute_magnitude(lw_vel)
rw_spd = compute_magnitude(rw_vel)


# 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()
```

[171]: <matplotlib.legend.Legend at 0x7fb6e5e4a820>



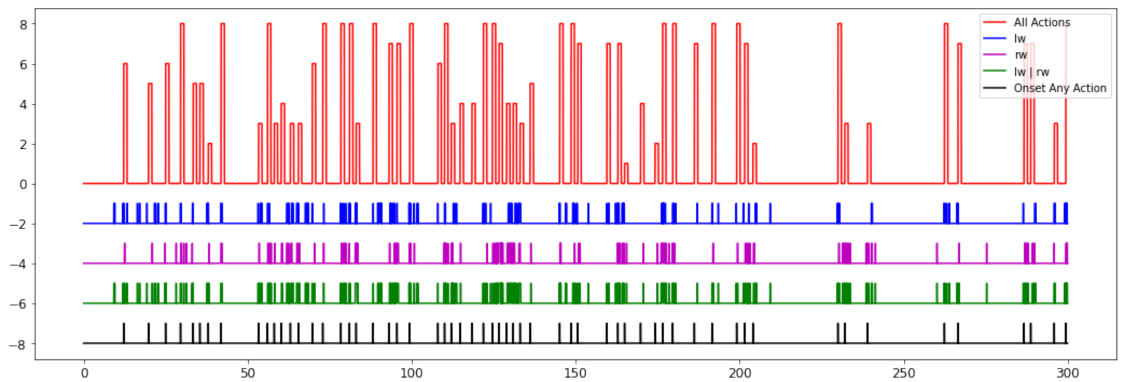
[172]:
```
""" PROVIDED
SPEED
Histograms of left vs right speeds for various motion categories
"""
fig, axs = plt.subplots(2,2, figsize=(FIGWIDTH,FIGHEIGHT))
fig.subplots_adjust(wspace=.35, hspace=.35)
axs = axs.ravel()
label_sets = (label_motion, label_onset_any, label_onset_l, label_onset_r)
label_sets_names = ('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()
```



[173]:
```
""" 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

#using list comprehension to fill with 0s and 1s
lw_spd_lbls = np.array([1 if i > .24 else 0 for i in lw_spd])

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

#using list comprehension to fill with 0s and 1s
```

```
rw_spd_lbls = np.array([1 if i > .13 else 0 for i in rw_spd])

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

#using list comprehension and zip to fill with 0s and 1s
spd_lbls = np.array([1 if i > .24 or j > .13 else 0 for i, j in zip(lw_spd,␣
↪rw_spd)])


# 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()
```

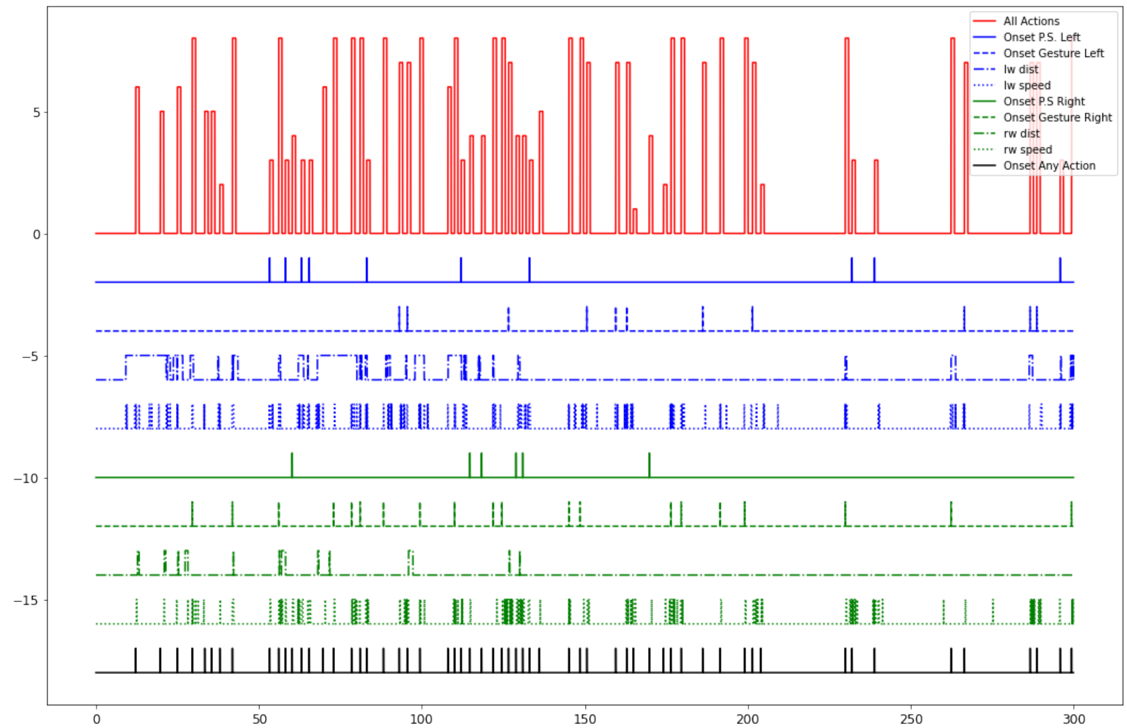
[173]: <matplotlib.legend.Legend at 0x7fb6ed04b970>



[174]:
```
""" 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')
```

```python
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()
```

[174]: <matplotlib.legend.Legend at 0x7fb6e6e825b0>

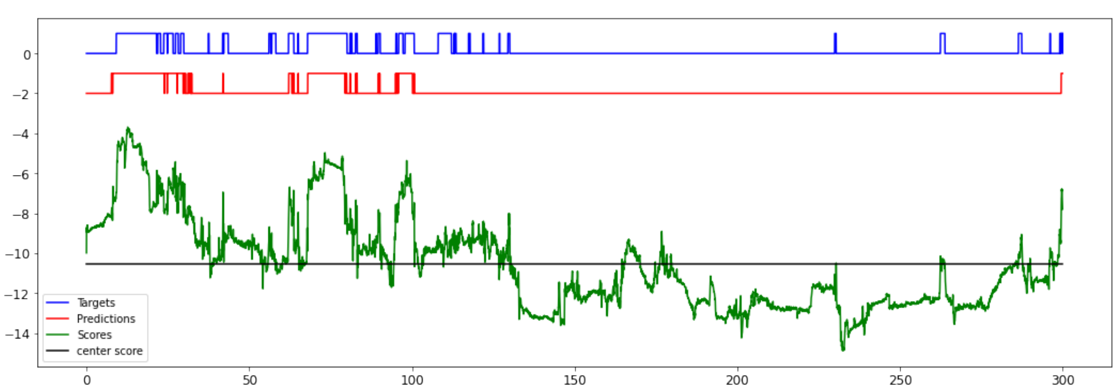


6 Classification Using Cross Validation

[180]:
```python
""" 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
```

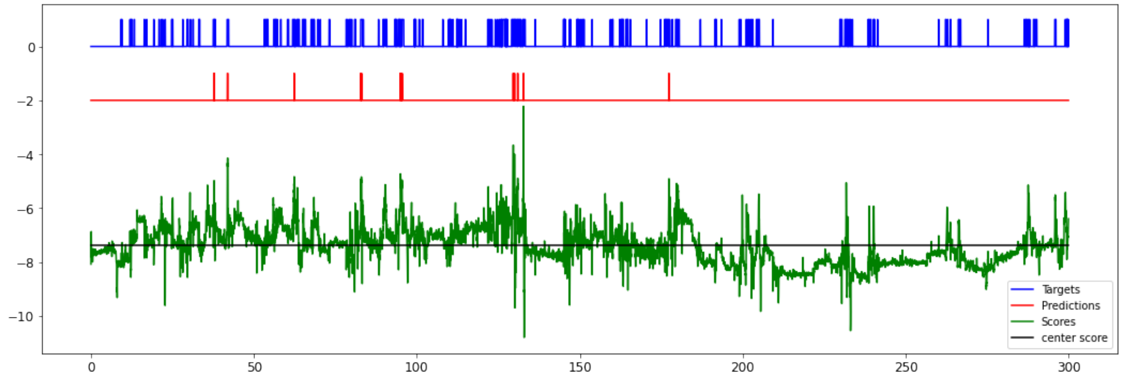
```
# TODO: Create and fit the classifer

#passing over what is in the comment above
clf = SGDClassifier(loss = 'log', random_state=42, max_iter=1e4, tol=1e-3)
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

#calling the imported function, passing the params specified
dist_scores = cross_val_predict(clf, X, y, cv=20, method='decision_function')

# TODO: use cross_val_predict() to compute the predicted labels by setting the␣
↪method
#       parameter equal to 'predict'. Please see the reference links above

#calling the imported function, passing the params specified
dist_preds = cross_val_predict(clf, X, y, cv=20, method='predict')


# 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()
```

[180]: <matplotlib.legend.Legend at 0x7fb6e5b526d0>



[181]:
```
""" 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

#passing over what is commented above
clf = SGDClassifier(loss='log', random_state=42, max_iter=10000, tol=1e-3)
# TODO: fit the classifier
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

#calling the imported function, passing the params specified
spd_scores = cross_val_predict(clf, X, y, cv=20, method='decision_function')

# TODO: use cross_val_predict() to compute the predicted labels by setting the␣
↪method
#       parameter equal to 'predict'. Please see the reference links above

#calling the imported function, passing the params specified
spd_preds = cross_val_predict(clf, X, y, cv=20, method='predict')


# 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()
```

[181]: <matplotlib.legend.Legend at 0x7fb6e5ac6d00>



7 Plotting Functions - Performance Results

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

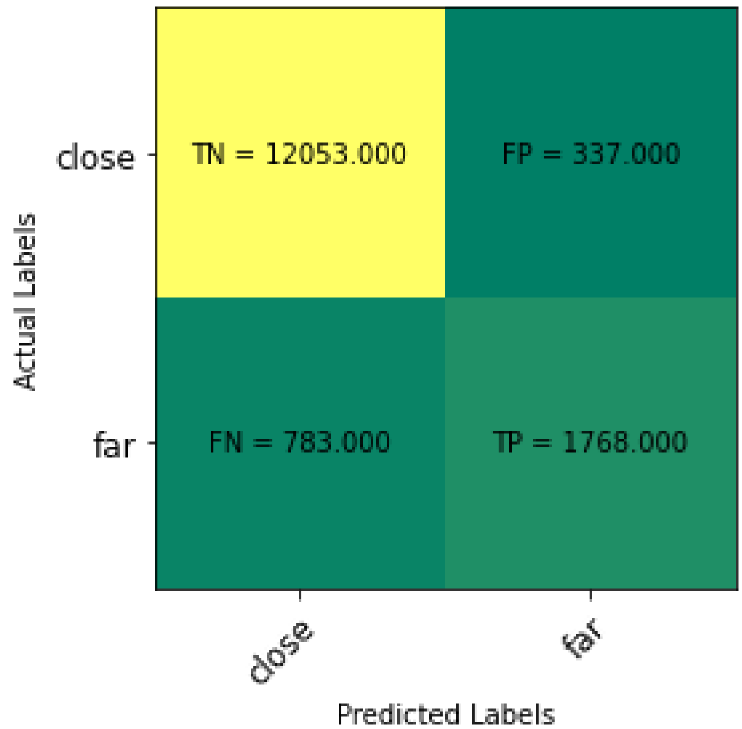
[182]:
```python
""" PROVIDED
"""
# Generate a color map plot for a confusion matrix
def confusion_mtx_colormap(mtx, xnames, ynames, cbarlabel=""):
    '''
    Generate a figure that plots a colormap of a matrix
    PARAMS:
        mtx: matrix of values
        xnames: list of x tick names
        ynames: list of the y tick names
        cbarlabel: label for the color bar
    RETURNS:
        fig, ax: the corresponding handles for the figure and axis
    '''
    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
```

```python
    ax.set_xticks(range(nxvars))
    ax.set_yticks(range(nyvars))
    ax.set_xticklabels(xnames)
    ax.set_yticklabels(ynames)
    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 the ROC Curve and the distributions of the
    TPR and FPR over a set of thresholds
    PARAMS:
        targets: list of true target labels
        scores: list of predicted labels or scores
    RETURNS:
        fpr: false positive rate
        tpr: true positive rate
        thresholds: thresholds used for the ROC curve
        auc: Area under the ROC Curve
        fig, axs: corresponding handles for the figure and axis
    '''
    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()
```

```python
    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_res, fig, axs
```

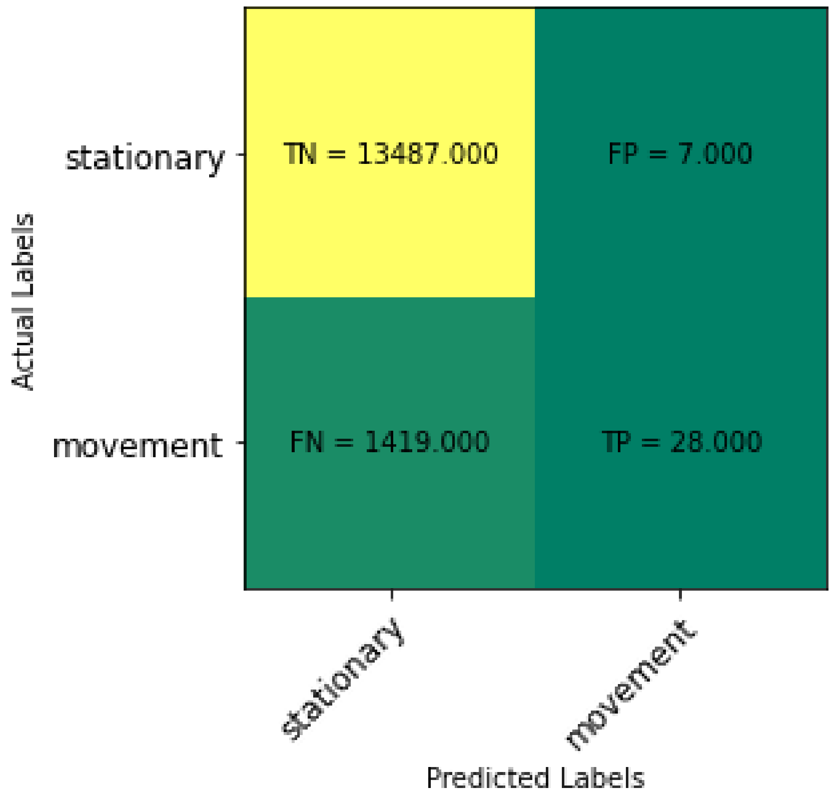
[183]:
```python
""" TODO
DISTANCE
Compute the confusion matrix using sklearn's confusion_matrix() function and
generate a color map using the provided confusion_mtx_colormap() for the model
built using the distance labels.
"""
label_names = ['close', 'far']

#calling imported function, passing over specified params
dist_confusion_mtx = confusion_matrix(dist_lbls, dist_preds)

# TODO: generate the confusion matrix color map

#calling function, passing params
confusion_mtx_colormap(dist_confusion_mtx, label_names, label_names)


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

[183]: (2551, 12390)



[184]:
```
""" 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']

#calling imported function, passing params
spd_confusion_mtx = confusion_matrix(spd_lbls, spd_preds)

# TODO: generate the confusion matrix color map

#calling function, passing params
confusion_mtx_colormap(spd_confusion_mtx, label_names,label_names)

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

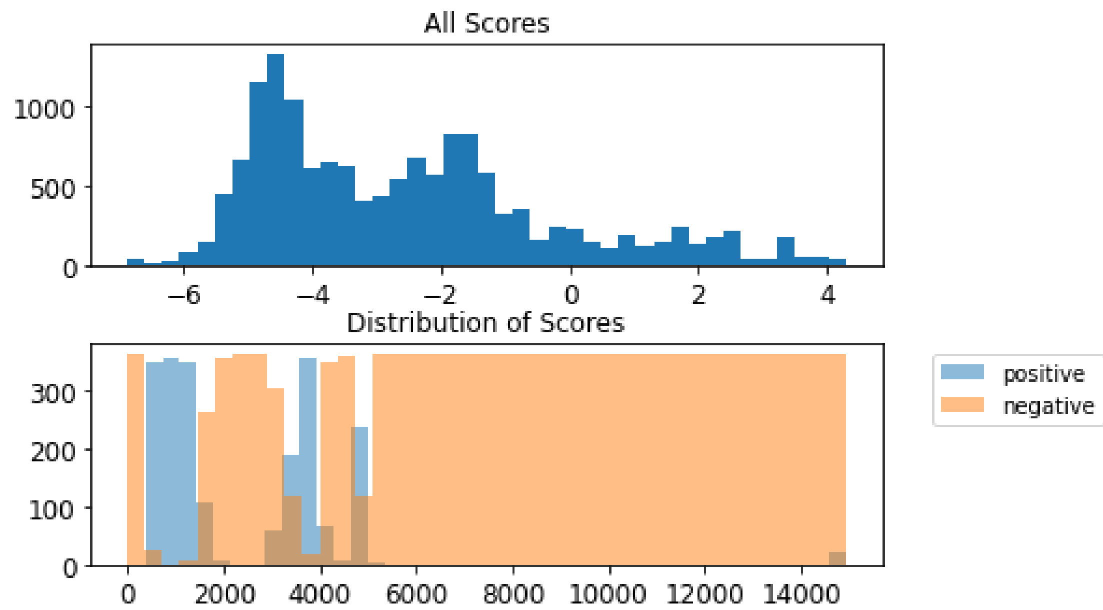
[184]: (1447, 13494)



[95]:
```
""" TODO
DISTANCE
Plot histograms of the scores from the model built using the distance labels.
Comparing distribution of scores for positive and 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. negative here means examples with a label of 0).
Use 41 as the number of bins.
See the lecture on classifiers for examples
"""

#creating two subplots
fig, axs = plt.subplots(2)
fig.tight_layout()

#plotting all scores
axs[0].set_title('All Scores')
axs[0].hist(dist_scores, bins=41)
```

```
#plotting with overlay labels with 1s and labels with 0s
axs[1].set_title('Distribution of Scores')
axs[1].hist(np.where(dist_preds==1), bins=41, alpha=.5, label='positive')
axs[1].hist(np.where(dist_preds==0), bins=41, alpha=.5, label='negative')
#moved legend to outsite to better show data
axs[1].legend(bbox_to_anchor=(1.05, 1))
```

[95]: <matplotlib.legend.Legend at 0x7fb6ec3399d0>



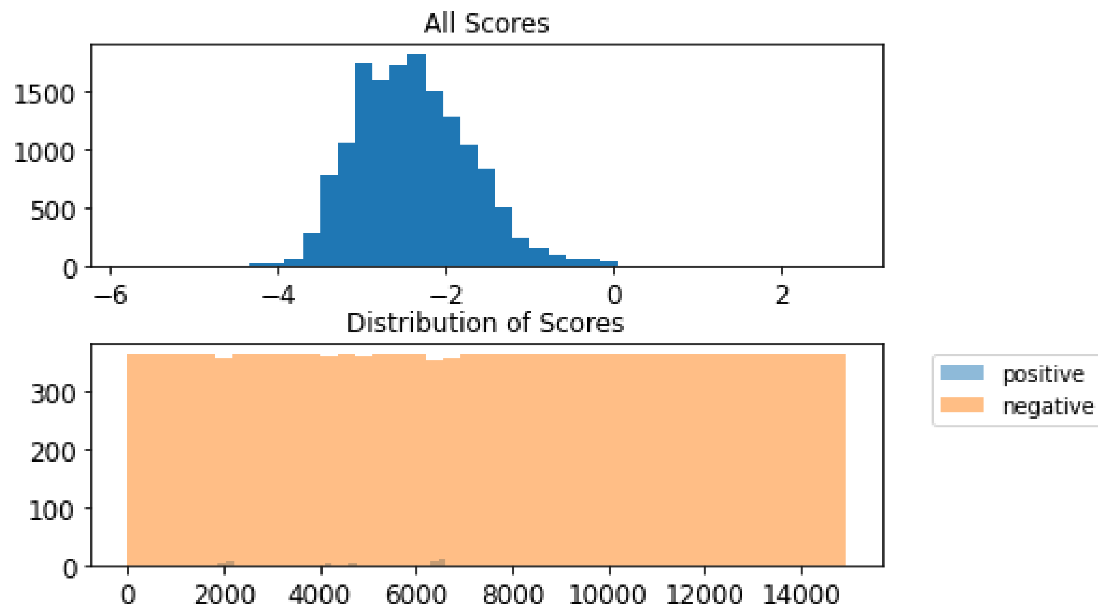
[94]:
```
""" TODO
SPEED
Plot histograms of the scores from the model built using the speed labels.
Comparing distribution of scores for positive ang negative examples.
Create one subplot of the distribution of all the scores.
Create a second subplot overlaying the distribution of the scores of the␣
↪positive
examples (i.e. positive here means examples with a label of 1) with the␣
↪distribution
of the negative examples (i.e. negative here means examples with a label of 0).
Use 41 as the number of bins.
See the lecture on classifiers for examples
"""

#creating two subplots
fig, axs = plt.subplots(2)
fig.tight_layout()
```

```
#plotting all scores
axs[0].set_title('All Scores')
axs[0].hist(spd_scores, bins=41)
#plotting with overlay labels with 1s and labels with 0s
axs[1].set_title('Distribution of Scores')
axs[1].hist(np.where(spd_preds==1), bins=41, alpha=.5, label='positive')
axs[1].hist(np.where(spd_preds==0), bins=41, alpha=.5, label='negative')
axs[1].legend(bbox_to_anchor=(1.05, 1))
```

```
[-3.08103785 -1.92685263 -2.40762441 … -1.68741809 -1.508863
 -1.39688691]
```

[94]:

```
<matplotlib.legend.Legend at 0x7fb6ec5421f0>
```



[108]:

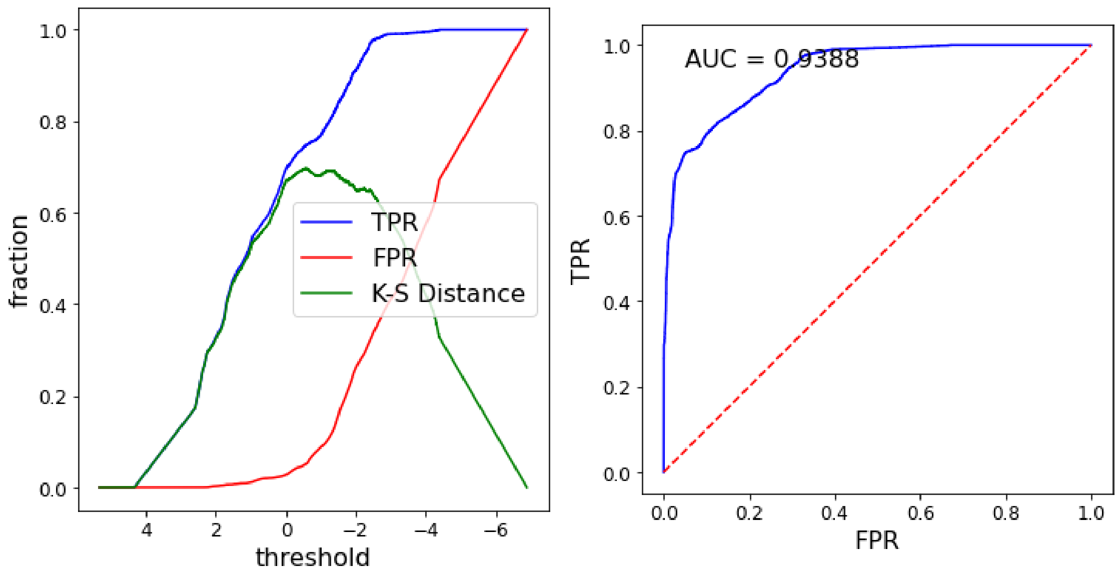
```
""" TODO
DISTANCE
Use ks_roc_plot() to plot the ROC curve and the KS plot for the model
constructed with the distance labels
"""

#calling function, passing params
ks_roc_plot(dist_lbls, dist_scores)
```

```
AUC: 0.9387806266291938
```

[108]:

```
(array([0.        , 0.        , 0.        , …, 0.67231638, 0.67231638,
        1.        ]),
```

```
array([0.00000000e+00, 3.92003136e-04, 1.73265386e-01, …,
       9.99607997e-01, 1.00000000e+00, 1.00000000e+00]),
array([ 5.30879049,  4.30879049,  2.5764396 , …, -4.38496692,
       -4.38531815, -6.8798203 ]),
0.9387806266291938,
<Figure size 864x432 with 2 Axes>,
array([<AxesSubplot:xlabel='threshold', ylabel='fraction'>,
       <AxesSubplot:xlabel='FPR', ylabel='TPR'>], dtype=object))
```

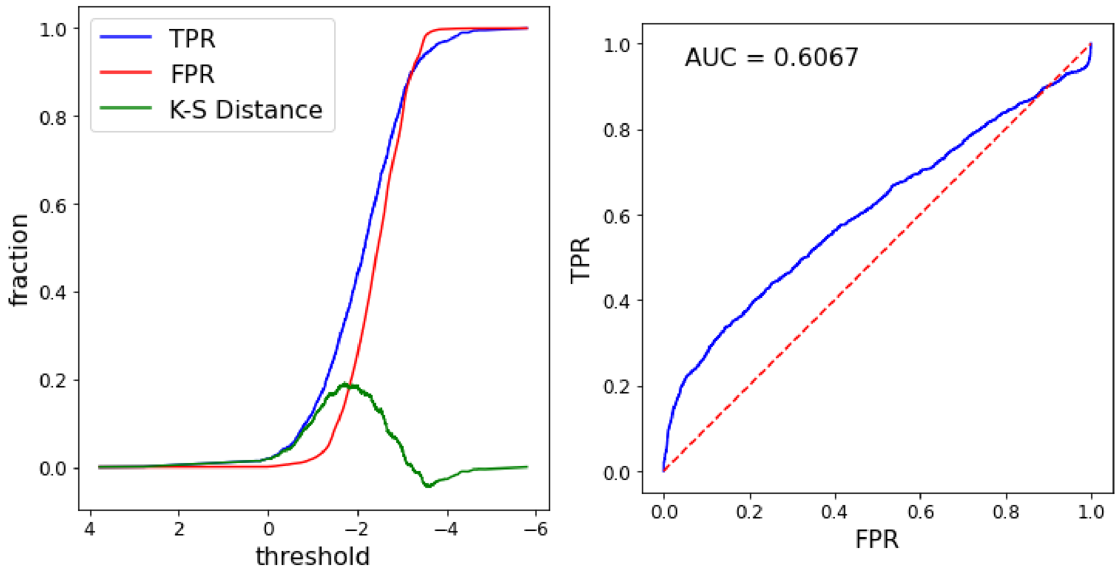


[109]:
```
""" TODO
SPEED
Use ks_roc_plot() to plot the ROC curve and the KS plot for the model
constructed with the speed labels
"""

#calling function, passing params
ks_roc_plot(spd_lbls, spd_scores)
```

```
AUC: 0.6066875661752046
```

[109]:
```
(array([0.        , 0.        , 0.        , …, 0.99977768, 1.        ,
        1.        ]),
 array([0.00000000e+00, 6.91085003e-04, 1.38217001e-02, …,
        9.95162405e-01, 9.95162405e-01, 1.00000000e+00]),
 array([ 3.77961032,  2.77961032,  0.27125085, …, -4.70495674,
        -4.86784857, -5.80394828]),
 0.6066875661752046,
 <Figure size 864x432 with 2 Axes>,
```

```
array([<AxesSubplot:xlabel='threshold', ylabel='fraction'>,
       <AxesSubplot:xlabel='FPR', ylabel='TPR'>], dtype=object))
```




```
[ ]:
```