Siamese CNN & OCSVM

Description

Reimplemenation of an approach to Continuous Authentication described by [1]. It leverages a Siamese CNN to generate Deep Features, which are then used as input for an OCSVM authentication classifier.

Purpose

- Test the approach with upfront global subject wise normalization (NAIVE_APPROACH)
- Change the normalization setting to be more realistic: Training data is normalized upfront again, but the Testing data is normalized using a single scaler fitted on training data only. (VALID_APPROACH)
- Identify parameters performing better in a valid setup than the parameters proposed by [1]. (ALTERNATIVE_APPROACH)

Data Sources

- [H-MOG Dataset (http://www.cs.wm.edu/~qyang/hmog.html)](http://www.cs.wm.edu/~qyang/hmog.html)

References

- [1] Centeno, M. P. et al. (2018): Mobile Based Continuous Authentication Using Deep Features. Proceedings of the 2^nd International Workshop on Embedded and Mobile Deep Learning (EMDL), 2018, 19-24.

1. Preparations

1.1 Imports

Note: The custom `DatasetLoader` is a helper class for easier loading and subsetting data from the datasets.

In [1]:
```
# Standard
from pathlib import Path
import os
import sys
import warnings
import random
import dataclasses
import math
import multiprocessing as mp

# Extra
import pandas as pd
import numpy as np
from sklearn import metrics
from sklearn.svm import OneClassSVM
from sklearn.model_selection import cross_validate, RandomizedSearchCV
from sklearn.decomposition import PCA
import statsmodels.stats.api as sms
import tensorflow as tf
from keras import backend as K
from keras.models import Model
from keras.layers import (
    Dense,
    Input,
    Conv1D,
    MaxPooling1D,
    Flatten,
    Lambda,
    Conv2D,
    MaxPooling2D,
    Dropout,
    BatchNormalization,
    GlobalAveragePooling1D,
    Activation
)
from keras.utils import plot_model
from keras.optimizers import Adam, SGD,RMSprop
from keras.models import load_model
from keras.callbacks import Callback
from tqdm.auto import tqdm
import seaborn as sns
```

```
import matplotlib.pyplot as plt
from IPython.display import display

# Custom
module_path = os.path.abspath(os.path.join(".."))  # supposed to be parent folder
if module_path not in sys.path:
    sys.path.append(module_path)
from src.utility.dataset_loader_hdf5 import DatasetLoader

# Global utitlity functions are loaded from separate notebook:
%run utils.ipynb
```

```
Using TensorFlow backend.
```

1.2 Configuration

In [2]:
```
# Configure Data Loading & Seed
SEED = 712  # Used for every random function
HMOG_HDF5 = Path.cwd().parent / "data" / "processed" / "hmog_dataset.hdf5"
EXCLUDE_COLS = ["sys_time"]
CORES = mp.cpu_count()

# For plots and CSVs
OUTPUT_PATH = Path.cwd() / "output" / "chapter-6-1-4-siamese-cnn"  # Cached data & csvs
OUTPUT_PATH.mkdir(parents=True, exist_ok=True)
REPORT_PATH = Path.cwd().parent / "reports" / "figures" # Figures for thesis
REPORT_PATH.mkdir(parents=True, exist_ok=True)

# Improve performance of Tensorflow (this improved speed _a_lot_ on my machine!!!)
K.tf.set_random_seed(SEED)
conf = K.tf.ConfigProto(
    device_count={"CPU": CORES},
    allow_soft_placement=True,
    intra_op_parallelism_threads=CORES,
    inter_op_parallelism_threads=CORES,
)
K.set_session(K.tf.Session(config=conf))

# Plotting
%matplotlib inline
utils_set_output_style()

# Silence various deprecation warnings...
tf.logging.set_verbosity(tf.logging.ERROR)
np.warnings.filterwarnings("ignore")
warnings.filterwarnings("ignore")
```

In [3]:
```
# Workaround to remove ugly spacing between tqdm progress bars:
HTML("<style>.p-Widget.jp-OutputPrompt.jp-OutputArea-prompt:empty{padding: 0;border: 0;}
div.output_subarea{padding:0;}</style>")
```

Out[3]:

1.3 Experiment Parameters

Selection of parameters set that had been tested in this notebook. Select one of them to reproduce results.

In [66]:
```
@dataclasses.dataclass
class ExperimentParameters:
    """Contains all relevant parameters to run an experiment."""

    name: str  # Name of Experiments Parameter set. Used as identifier for charts etc.

    # Data / Splitting:
    frequency: int
    feature_cols: list  # Columns used as features
    max_subjects: int
    exclude_subjects: list  # Don't load data from those users
    n_valid_train_subjects: int
    n_valid_test_subjects: int
    n_test_train_subjects: int
    n_test_test_subjects: int
    seconds_per_subject_train: float
    seconds_per_subject_test: float
    task_types: list  # Limit scenarios to [1, 3, 5] for sitting or [2, 4, 6] for walking, or don't limit
(None)

    # Reshaping
    window_size: int  # After resampling
    step_width: int  # After resampling

    # Normalization
    scaler: str  # {"std", "robust", "minmax"}
    scaler_scope: str  # {"subject", "session"}
    scaler_global: bool  # scale training and testing sets at once (True), or fit scaler on training only
(False)

    # Siamese Network
    max_pairs_per_session: int  # Max. number of pairs per session
    margin: float  # Contrastive Loss Margin
    model_variant: str  # {"1d", "2d"} Type of architecture
    filters: list  # List of length 4, containing number of filters for conv layers
    epochs_best: int  # Train epochs to for final model
    epochs_max: int
    batch_size: int
    optimizer: str  # Optimizer to use for Siamese Network
    optimizer_lr: float  # Learning Rate
    optimizer_decay: float
```

```
    # OCSVM
    ocsvm_nu: float  # Best value found in random search, used for final model
    ocsvm_gamma: float  # Best value found in random search, used for final model

    # Calculated values
    def __post_init__(self):
        # HDF key of table:
        self.table_name = f"sensors_{self.frequency}hz"

        # Number of samples per _session_ used for training:
        self.samples_per_subject_train = math.ceil(
            (self.seconds_per_subject_train * 100)
            / (100 / self.frequency)
            / self.window_size
        )

        # Number of samples per _session_ used for testing:
        self.samples_per_subject_test = math.ceil(
            (self.seconds_per_subject_test * 100)
            / (100 / self.frequency)
            / self.window_size
        )


# INSTANCES
# ===========================================================

# NAIVE_MINMAX (2D Filters)
# -----------------------------------------------------------
NAIVE_MINMAX_2D = ExperimentParameters(
    name="NAIVE-MINMAX-2D",
    # Data / Splitting
    frequency=25,
    feature_cols=[
        "acc_x",
        "acc_y",
        "acc_z",
        "gyr_x",
        "gyr_y",
        "gyr_z",
        "mag_x",
```

```
        "mag_y",
        "mag_z",
    ],
    max_subjects=90,
    exclude_subjects=[
        "733162",  # No 24 sessions
        "526319",  # ^
        "796581",  # ^
        "539502",  # Least amount of sensor values
        "219303",  # ^
        "737973",  # ^
        "986737",  # ^
        "256487",  # Most amount of sensor values
        "389015",  # ^
        "856401",  # ^
    ],
    n_valid_train_subjects=40,
    n_valid_test_subjects=10,
    n_test_train_subjects=10,
    n_test_test_subjects=30,
    seconds_per_subject_train=67.5,
    seconds_per_subject_test=67.5,
    task_types=None,
    # Reshaping
    window_size=25,  # 1 sec
    step_width=25,
    # Normalization
    scaler="minmax",
    scaler_scope="subject",
    scaler_global=True,
    # Siamese Network
    model_variant="2d",
    filters=[32, 64, 128, 32],
    epochs_best=35,
    epochs_max=40,
    batch_size=200,
    optimizer="sgd",
    optimizer_lr=0.01,
    optimizer_decay=0,
    max_pairs_per_session=60,  # => 4min
    margin=0.2,
    # OCSVM
```

```
    ocsvm_nu=0.092,
    ocsvm_gamma=1.151,
)  # <END NAIVE_APPROACH>

# VALID_MINMAX (2D)
# ------------------------------------------------------------
VALID_MINMAX_2D = dataclasses.replace(
    NAIVE_MINMAX_2D,
    name="VALID-MINMAX-2D",
    task_types=None,
    scaler_global=False,
    epochs_max=40,
    ocsvm_nu=0.110,
    ocsvm_gamma=59.636,
)

# NAIVE_ROBUST (2D)
# ------------------------------------------------------------
NAIVE_ROBUST_2D = dataclasses.replace(
    NAIVE_MINMAX_2D,
    name="NAIVE-ROBUST-2D",
    scaler="robust",
    optimizer="sgd",
    optimizer_lr=0.05, # Decreased, to avoid "all zeros" prediction
    optimizer_decay=0.002,
    epochs_best=5,
    ocsvm_nu=0.214,
    ocsvm_gamma=2.354,
)

# VALID_ROBUST (2D)
# ------------------------------------------------------------
VALID_ROBUST_2D = dataclasses.replace(
    NAIVE_MINMAX_2D,
    name="VALID-ROBUST-2D",
    scaler="robust",
    scaler_global=False,
    epochs_best=6,
    epochs_max=20,
    optimizer="sgd",
    optimizer_lr=0.05,  # Decrease LR, to avoid "all zeros" prediction
    optimizer_decay=0.002,
```

```
    ocsvm_nu=0.190,
    ocsvm_gamma=0.069,
)

# VALID_ROBUST (1D)
# ------------------------------------------------------------
VALID_ROBUST_1D = dataclasses.replace(
    NAIVE_MINMAX_2D,
    name="VALID-ROBUST-1D",
    scaler="robust",
    scaler_global=False,
    model_variant="1d",
    filters=[32, 64, 128, 64],
    epochs_best=9,
    epochs_max=20,
    ocsvm_nu=0.156,
    ocsvm_gamma=33.932,
)

# FCN_ROBUST (1D)
# ------------------------------------------------------------
VALID_FCN_ROBUST = dataclasses.replace(
    NAIVE_MINMAX_2D,
    name="VALID-FCN-ROBUST-FINAL",
    task_types=[2, 4, 6],
    feature_cols=["acc_x", "acc_y", "acc_z"],
    frequency=25,
    window_size=25*5,
    step_width=25*5,
    scaler="robust",
    scaler_global=False,
    seconds_per_subject_train=60 * 10,
    seconds_per_subject_test=60 * 10,
    max_pairs_per_session=60 * 10,
    model_variant="fcn",
    filters=[32, 64, 32],
    optimizer="adam",
    optimizer_lr=0.001,
    optimizer_decay=None,
    batch_size=300,
    margin=1,
    epochs_best=40,
```

```
    epochs_max=80,
    ocsvm_nu=0.165,
    ocsvm_gamma=8.296,
)
```

1.4 Select Approach

Select the parameters to use for current notebook execution here!

In [67]:
```
P = VALID_FCN_ROBUST
```

Overview of current Experiment Parameters:

In [68]:
```
utils_ppp(P)
```

	Value
batch_size	300
epochs_best	40
epochs_max	80
exclude_subjects	[733162, 526319, 796581, 539502, 219303, 73797...
feature_cols	[acc_x, acc_y, acc_z]
filters	[32, 64, 32]
frequency	25
margin	1
max_pairs_per_session	600
max_subjects	90
model_variant	fcn
n_test_test_subjects	30
n_test_train_subjects	10
n_valid_test_subjects	10
n_valid_train_subjects	40
name	VALID-FCN-ROBUST-FINAL
ocsvm_gamma	8.296
ocsvm_nu	0.165
optimizer	adam
optimizer_decay	None
optimizer_lr	0.001
scaler	robust
scaler_global	False
scaler_scope	subject

	Value
seconds_per_subject_test	600
seconds_per_subject_train	600
step_width	125
task_types	[2, 4, 6]
window_size	125

2. Initial Data Preparation

2.1 Load Dataset

In [7]:

```
hmog = DatasetLoader(
    hdf5_file=HMOG_HDF5,
    table_name=P.table_name,
    max_subjects=P.max_subjects,
    task_types=P.task_types,
    exclude_subjects=P.exclude_subjects,
    exclude_cols=EXCLUDE_COLS,
    seed=SEED,
)
hmog.data_summary()
```

```
HBox(children=(IntProgress(value=0, description='Loading sessions', max=1080, style=ProgressStyle(description
_…
```

Out[7]:

	DataFrame	Memory (MB)	Rows	Columns	Subjects	Sessions
0	all	1437.64	14494937	12	90	1080
1	index	0.08	2160	4	90	2160

2.2 Normalize Features (if global)

Used here for naive approach (before splitting into test and training sets). Otherwise it's used during generate_pairs() and respects train vs. test borders.

In [8]:
```
if P.scaler_global:
    print("Normalize all data before splitting into train and test sets...")
    hmog.all, scalers = utils_custom_scale(
        hmog.all,
        scale_cols=P.feature_cols,
        feature_cols=P.feature_cols,
        scaler_name=P.scaler,
        scope=P.scaler_scope,
        plot=True,
    )
else:
    print("Skipped, normalize after splitting.")
```

```
Skipped, normalize after splitting.
```

2.3 Split Dataset for Valid/Test

In two splits: one used during hyperparameter optimization, and one used during testing.

The split is done along the subjects: All sessions of a single subject will either be in the validation split or in the testing split, never in both.

In [9]:
```
hmog.split_train_valid_train_test(
    n_valid_train=P.n_valid_train_subjects,
    n_valid_test=P.n_valid_test_subjects,
    n_test_train=P.n_test_train_subjects,
    n_test_test=P.n_test_test_subjects,
)
hmog.data_summary()
```

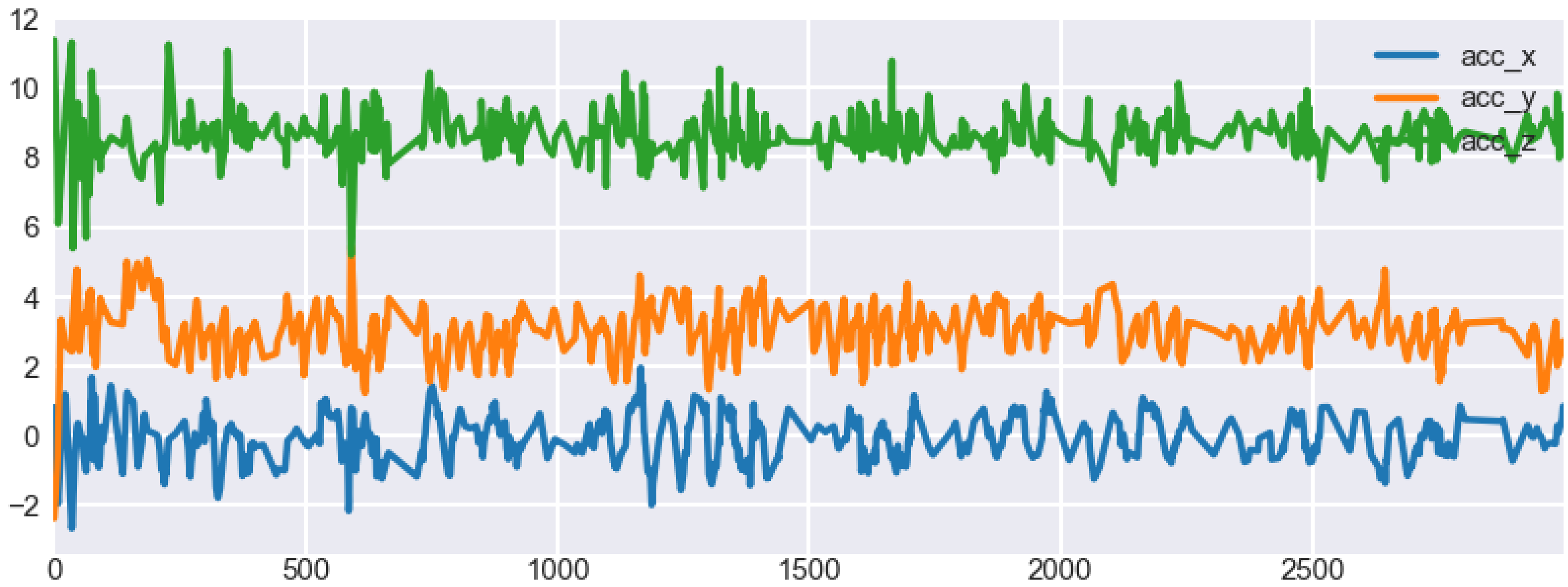
Out[9]:

	DataFrame	Memory (MB)	Rows	Columns	Subjects	Sessions
0	index	0.08	2160	4	90	2160
1	valid_train	656.86	6622762	12	40	480
2	valid_test	169.38	1707776	12	10	120
3	test_train	145.71	1469069	12	10	120
4	test_test	465.69	4695330	12	30	360

2.4 Normalize features (if not global)

In [10]:
```
if not P.scaler_global:
    print("Scaling Data for Siamese Network only...")
    print("Training Data:")
    hmog.valid_train, _ = utils_custom_scale(
        hmog.valid_train,
        scale_cols=P.feature_cols,
        feature_cols=P.feature_cols,
        scaler_name=P.scaler,
        scope=P.scaler_scope,
        plot=True,
    )
    print("Validation Data:")
    hmog.valid_test, _ = utils_custom_scale(
        hmog.valid_test,
        scale_cols=P.feature_cols,
        feature_cols=P.feature_cols,
        scaler_name=P.scaler,
        scope=P.scaler_scope,
        plot=True,
    )
else:
    print("Skipped, already normalized.")
```

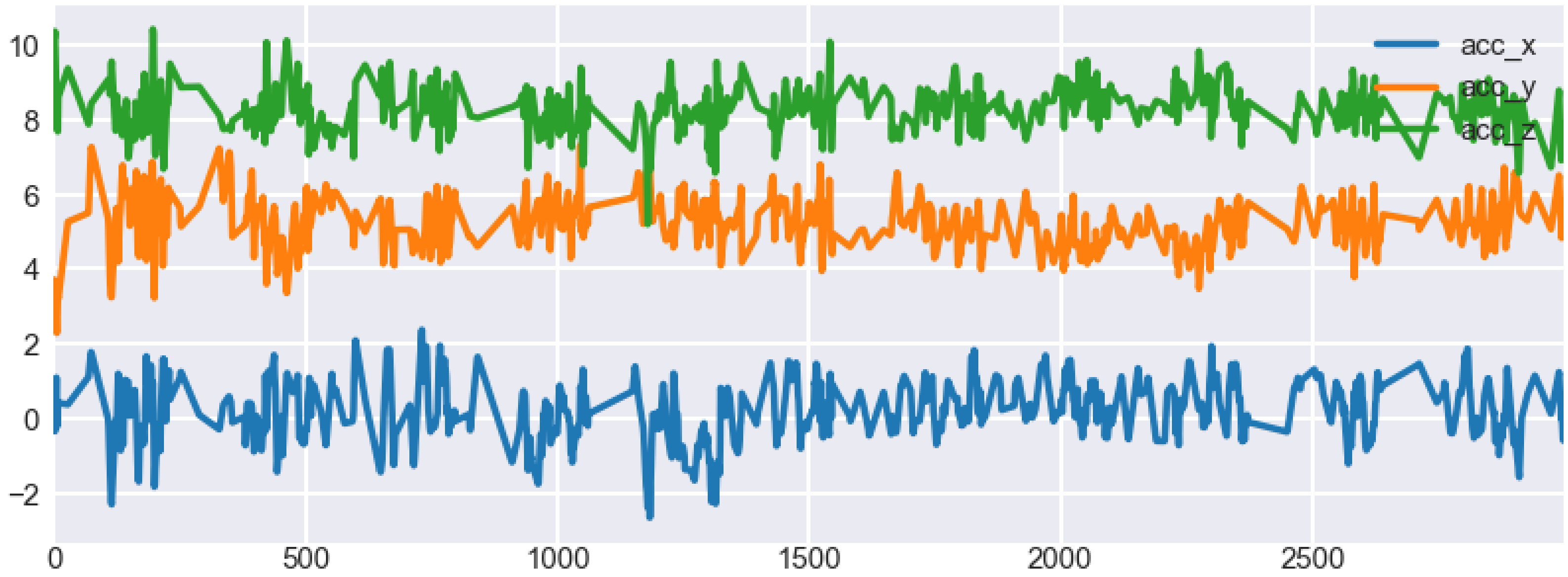
```
Scaling Data for Siamese Network only...
Training Data:
Before Scaling:
```




```
HBox(children=(IntProgress(value=0, description='subjects', max=40, style=ProgressStyle(description_width='in
i…
```

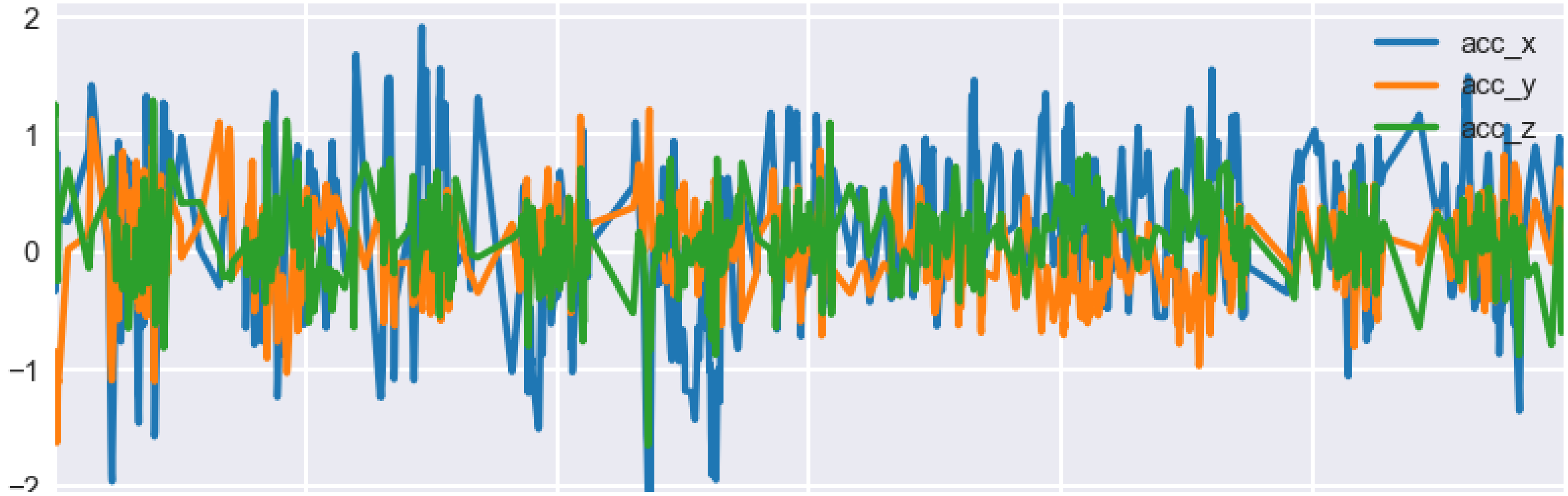
```
After Scaling:
```

```
Validation Data:
Before Scaling:
```




```
HBox(children=(IntProgress(value=0, description='subjects', max=10, style=ProgressStyle(description_width='in
i…
```

```
After Scaling:
```



2.5 Check Splits

In [11]:
```
utils_split_report(hmog.valid_train)
```

```
Unique subjects: 40
Unique sessions: 480

Head:
```

	acc_x	acc_y	acc_z	gyr_x	gyr_y	gyr_z	mag_x	mag_y	mag_z	subject	session	task_type
0	1.126539	-5.676733	3.232535	0.544714	-0.159665	0.029449	6.826999	32.188268	8.67	100669	100669_session_12	6
1	0.726045	-5.490228	2.748784	0.621841	-0.121316	0.017797	7.146999	31.996983	8.67	100669	100669_session_12	6
2	0.325552	-5.303724	2.265033	0.698968	-0.082967	0.006145	7.466999	31.805697	8.67	100669	100669_session_12	6
3	-0.074942	-5.117219	1.781282	0.776096	-0.044619	-0.005506	7.786999	31.614411	8.67	100669	100669_session_12	6
4	-0.475436	-4.930714	1.297531	0.853223	-0.006270	-0.017158	8.106999	31.423126	8.67	100669	100669_session_12	6

```
Sessions' Task Types per subject:
```

subject	100669	171538	201848	220962	261313	277905	278135	326223	342329	366286	368258	395129	398248	472761	489146	525584	527
2	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	
4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	
6	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	

In [12]:
```
utils_split_report(hmog.valid_test)
```

```
Unique subjects: 10
Unique sessions: 120

Head:
```

	acc_x	acc_y	acc_z	gyr_x	gyr_y	gyr_z	mag_x	mag_y	mag_z	subject	session	task_type
0	-0.042820	-0.841897	1.159331	0.418076	-0.425025	0.154106	7.509463	5.205567	-35.976860	257279	257279_session_1	6
1	-0.335043	-1.059704	1.256299	0.524367	-0.296209	0.229930	7.434780	4.952402	-35.692659	257279	257279_session_1	6
2	0.061697	-1.233816	0.944090	0.430375	-0.343123	0.151413	7.514585	4.670094	-35.519911	257279	257279_session_1	6
3	0.458436	-1.407928	0.631880	0.336383	-0.390037	0.072897	7.594390	4.387785	-35.347163	257279	257279_session_1	6
4	0.855176	-1.582041	0.319670	0.202306	-0.300045	-0.043262	7.674195	4.105476	-35.174415	257279	257279_session_1	6

```
Sessions' Task Types per subject:
```

subject	257279	396697	554303	594887	621276	733568	777078	815316	923862	984799
2	4	4	4	4	4	4	4	4	4	4
4	4	4	4	4	4	4	4	4	4	4
6	4	4	4	4	4	4	4	4	4	4

In [13]:
```
utils_split_report(hmog.test_train)
```

```
Unique subjects: 10
Unique sessions: 120

Head:
```

	acc_x	acc_y	acc_z	gyr_x	gyr_y	gyr_z	mag_x	mag_y	mag_z	subject	session	task_type
0	1.397885	6.634745	8.873776	0.097367	-0.261735	0.130239	2.587439	-11.002091	-11.930931	207696	207696_session_11	2
1	1.256549	6.640633	8.687734	0.146060	-0.184967	-0.084313	2.503170	-11.222939	-11.932120	207696	207696_session_11	2
2	1.115212	6.646520	8.501693	0.001951	-0.150648	-0.155729	2.424210	-11.444220	-11.929560	207696	207696_session_11	2
3	0.973876	6.652407	8.315652	-0.142158	-0.116328	-0.227145	2.345250	-11.665500	-11.927000	207696	207696_session_11	2
4	0.832540	6.658295	8.129611	-0.286267	-0.082009	-0.298561	2.266290	-11.886780	-11.924440	207696	207696_session_11	2

```
Sessions' Task Types per subject:
```

subject	207696	240168	352716	431312	578526	622852	776328	785899	856302	980953
2	4	4	4	4	4	4	4	4	4	4
4	4	4	4	4	4	4	4	4	4	4
6	4	4	4	4	4	4	4	4	4	4

In [14]:
```
utils_split_report(hmog.test_test)
```

```
Unique subjects: 30
Unique sessions: 360

Head:
```

	acc_x	acc_y	acc_z	gyr_x	gyr_y	gyr_z	mag_x	mag_y	mag_z	subject	session	task_type
0	-0.376539	3.110742	7.732258	-0.042379	-0.081758	-0.053667	-29.872625	11.404750	-37.032375	151985	151985_session_10	6
1	-0.376673	3.125309	7.726362	-0.047065	-0.074980	-0.064833	-29.868323	11.511205	-37.468728	151985	151985_session_10	6
2	-0.376807	3.139875	7.720466	-0.051750	-0.068202	-0.075998	-29.872394	11.623124	-37.545312	151985	151985_session_10	6
3	-0.376941	3.154442	7.714570	-0.056435	-0.061424	-0.087164	-29.878560	11.736408	-37.531954	151985	151985_session_10	6
4	-0.377076	3.169009	7.708674	-0.061120	-0.054646	-0.098329	-29.884725	11.849693	-37.518596	151985	151985_session_10	6

```
Sessions' Task Types per subject:
```

subject	151985	180679	186676	218719	248252	264325	336172	405035	501973	553321	561993	579284	663153	675397	717868	720193	751
2	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	
4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	
6	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	

2.6 Reshape Features

Reshape & cache Set for Training Siamese Network:

In [15]:
```
df_siamese_train = utils_reshape_features(
    hmog.valid_train,
    feature_cols=P.feature_cols,
    window_size=P.window_size,
    step_width=P.step_width,
)

# Clean memory
del hmog.train
%reset_selective -f hmog.train

print("Validation data after reshaping:")
display(df_siamese_train.head())

# Store iterim data
df_siamese_train.to_msgpack(OUTPUT_PATH / "df_siamese_train.msg")

# Clean memory
%reset_selective -f df_siamese_train
```

```
HBox(children=(IntProgress(value=0, description='Session', max=480, style=ProgressStyle(description_width='in
i…

Validation data after reshaping:
```

	X	subject	session	task_type
0	[[1.126538556309365, -5.676733181236054, 3.232...	100669	100669_session_12	6
1	[[0.35454249979518676, -1.2795481927044285, 0....	100669	100669_session_12	6
2	[[0.5150551243002253, -1.6982955451723616, 0.6...	100669	100669_session_12	6
3	[[-0.9393853286507788, -2.2431333573807604, 1....	100669	100669_session_12	6
4	[[0.00042849556207466284, -2.142130982688511, ...	100669	100669_session_12	6

Reshape & cache Set for Validating Siamese Network: (also used to optimize OCSVM)

In [16]:
```
df_siamese_valid = utils_reshape_features(
    hmog.valid_test,
    feature_cols=P.feature_cols,
    window_size=P.window_size,
    step_width=P.step_width,
)

del hmog.valid
%reset_selective -f hmog.valid

print("Testing data after reshaping:")
display(df_siamese_valid.head())

# Store iterim data
df_siamese_valid.to_msgpack(OUTPUT_PATH / "df_siamese_valid.msg")

# Clean memory
%reset_selective -f df_siamese_valid
```

```
HBox(children=(IntProgress(value=0, description='Session', max=120, style=ProgressStyle(description_width='in
i…

Testing data after reshaping:
```

	X	subject	session	task_type
0	[[-0.04281976952530689, -0.8418968191771367, 1...	257279	257279_session_1	6
1	[[0.13079446862052027, 0.10234259964161609, 0....	257279	257279_session_1	6
2	[[0.8587300291499387, 0.22569888511439404, 0.4...	257279	257279_session_1	6
3	[[-0.027996045361265667, -0.05663118972213963,...	257279	257279_session_1	6
4	[[-0.25892495983972386, 0.3904236255845561, 0....	257279	257279_session_1	6

Reshape & cache Set for Training/Validation OCSVM:

In [17]:
```
df_ocsvm_train_valid = utils_reshape_features(
    hmog.test_train,
    feature_cols=P.feature_cols,
    window_size=P.window_size,
    step_width=P.step_width,
)

del hmog.test_train
%reset_selective -f hmog.test_train

print("Testing data after reshaping:")
display(df_ocsvm_train_valid.head())

# Store iterim data
df_ocsvm_train_valid.to_msgpack(OUTPUT_PATH / "df_ocsvm_train_valid.msg")

# Clean memory
%reset_selective -f df_ocsvm_train_valid
```

```
HBox(children=(IntProgress(value=0, description='Session', max=120, style=ProgressStyle(description_width='in
i…

Testing data after reshaping:
```

	X	subject	session	task_type
0	[[1.3978850635805664, 6.634745158553127, 8.873...	207696	207696_session_11	2
1	[[0.8989105212499999, 7.4393458625, 5.20084218...	207696	207696_session_11	2
2	[[-0.8528512094444445, 5.462304877777777, 7.74...	207696	207696_session_11	2
3	[[-2.062305483175016, 4.1703999289186555, 7.23...	207696	207696_session_11	2
4	[[-0.9964742910047201, 4.9818725305168, 8.2125...	207696	207696_session_11	2

Reshape & cache Set for Training/Testing OCSVM:

In [18]:
```
df_ocsvm_train_test = utils_reshape_features(
    hmog.test_test,
    feature_cols=P.feature_cols,
    window_size=P.window_size,
    step_width=P.step_width,
)

del hmog.test_test
%reset_selective -f hmog.test_test

print("Testing data after reshaping:")
display(df_ocsvm_train_test.head())

# Store iterim data
df_ocsvm_train_test.to_msgpack(OUTPUT_PATH / "df_ocsvm_train_test.msg")

# Clean memory
%reset_selective -f df_ocsvm_train_test
%reset_selective -f df_
```

```
HBox(children=(IntProgress(value=0, description='Session', max=360, style=ProgressStyle(description_width='in
i…
```

```
Testing data after reshaping:
```

	X	subject	session	task_type
0	[[-0.3765385456074766, 3.1107421714953274, 7.7...	151985	151985_session_10	6
1	[[0.09549826478869189, 3.9700954602219136, 7.7...	151985	151985_session_10	6
2	[[0.20883461625482397, 3.2271731154792, 8.6506...	151985	151985_session_10	6
3	[[0.0038022012564349096, 3.0280049158538764, 9...	151985	151985_session_10	6
4	[[-2.4728418720348535, 3.5376784001577266, 7.4...	151985	151985_session_10	6

3. Generate Scenario Pairs

3.1 Load cached Data

In [19]:
```
df_siamese_train = pd.read_msgpack(OUTPUT_PATH / "df_siamese_train.msg")
df_siamese_valid = pd.read_msgpack(OUTPUT_PATH / "df_siamese_valid.msg")
```

3.2 Build positive/negative Pairs

In [20]:
```
def build_pairs(df):
    # Limit samples per subject to sample of shortest session
    df = df.groupby("session", group_keys=False).apply(
        lambda x: x.sample(min(len(x), P.max_pairs_per_session), random_state=SEED)
    )
    df_pairs = None

    # Split samples subject wise 50:50
    # ---------------
    df_positives = None
    df_negatives = None

    for subject in df["subject"].unique():
        # Shuffle
        df_subj = df[df["subject"] == subject].sample(frac=1, random_state=SEED)

        # Make rows even
        if len(df_subj) % 2 != 0:
            df_subj = df_subj.iloc[:-1]

        half = len(df_subj) // 2

        df_positives = pd.concat([df_positives, df_subj.iloc[:half]])
        df_negatives = pd.concat([df_negatives, df_subj.iloc[half:]])

    # Positive Pairs
    # ---------------
    df_positive_left = None
    df_positive_right = None

    for subject in df_positives["subject"].unique():
        df_subj = df[df["subject"] == subject]
        # Make rows even
        if len(df_subj) % 2 != 0:
            df_subj = df_subj.iloc[:-1]

        # Split in half
        half = len(df_subj) // 2
        df_positive_left = pd.concat([df_positive_left, df_subj.iloc[:half]])
        df_positive_right = pd.concat([df_positive_right, df_subj.iloc[half:]])
```

```
    df_positive_left = df_positive_left.reset_index(drop=True)
    df_positive_right = df_positive_right.reset_index(drop=True)
    df_positive_left.columns = ["left_" + c for c in df_positive_left.columns]
    df_positive_right.columns = ["right_" + c for c in df_positive_right.columns]

    df_positives = pd.concat(
        [df_positive_left, df_positive_right],
        axis=1,
        sort=False,
        join_axes=[df_positive_left.index],
    )

    # Negative Pairs
    # ---------------
    # Make rows even
    if len(df_negatives) % 2 != 0:
        df_negatives = df_negatives.iloc[:-1]

    # Split in half
    half = len(df_negatives) // 2
    df_negative_left = df_negatives.iloc[half:].reset_index(drop=True)
    df_negative_right = df_negatives.iloc[:half].reset_index(drop=True)

    # Name columns
    df_negative_left.columns = ["left_" + c for c in df_negative_left.columns]
    df_negative_right.columns = ["right_" + c for c in df_negative_right.columns]

    # Combine
    df_negatives = pd.concat(
        [df_negative_left, df_negative_right],
        axis=1,
        sort=False,
        join_axes=[df_negative_left.index],
    )

    # Combine both Pairs
    # ---------------
    # Balance pairs
    min_len = min(len(df_positives), len(df_negatives))
    df_positives = df_positives.sample(n=min_len, random_state=SEED)
    df_negatives = df_negatives.sample(n=min_len, random_state=SEED)
```

```
    # Combine
    df_pairs = pd.concat([df_positives, df_negatives], sort=False)

    # Shuffle
    df_pairs = df_pairs.sample(frac=1, random_state=SEED).reset_index(drop=True)

    # Set Label
    df_pairs["label"] = np.where(
        df_pairs["left_subject"] == df_pairs["right_subject"], 1, 0
    )

    return df_pairs
```

In [21]:
```
# Reduce observations/samples per
print("Sample per session before reduction:\n ")
display(df_siamese_train["session"].value_counts().head(3))
display(df_siamese_valid["session"].value_counts().head(3))

df_siamese_train = df_siamese_train.groupby("session", group_keys=False).apply(
    lambda x: x.sample(n=min(len(x), P.samples_per_subject_train), random_state=SEED)
)

df_siamese_valid = df_siamese_valid.groupby("session", group_keys=False).apply(
    lambda x: x.sample(n=min(len(x), P.samples_per_subject_test), random_state=SEED)
)

print("\n\nSample per session after reduction:\n")
display(df_siamese_train["session"].value_counts().head(3))
display(df_siamese_valid["session"].value_counts().head(3))
```

```
Sample per session before reduction:


527796_session_2    387
876011_session_4    339
278135_session_2    312
Name: session, dtype: int64

733568_session_2    417
396697_session_1    330
621276_session_1    286
Name: session, dtype: int64



Sample per session after reduction:


527796_session_23    120
201848_session_18    120
763813_session_21    120
Name: session, dtype: int64

923862_session_3     120
396697_session_20    120
```

```
396697_session_2     120
Name: session, dtype: int64
```

In [22]:
```
df_siamese_train_pairs = build_pairs(df_siamese_train)
df_siamese_valid_pairs = build_pairs(df_siamese_valid)
```

3.3 Inspect Pairs

In [23]:
```
print("DataFrame Info:")
display(df_siamese_train_pairs.info())

print("\n\nHead:")
display(df_siamese_train_pairs.head(5))

print("\n\nAny NaN values?")
display(df_siamese_train_pairs.isnull().sum(axis = 0))

df_left_sub = df_siamese_train_pairs.groupby("left_subject")["left_subject"].count()
df_right_sub = df_siamese_train_pairs.groupby("right_subject")["right_subject"].count()
df_temp = pd.concat([df_left_sub, df_right_sub])

print("\n\n\nDistribution of Samples per Subjects in training Data")

fig, axes = plt.subplots(
    ncols=2, nrows=1, figsize=(5.473, 2), dpi=180, gridspec_kw={"width_ratios": [1, 5]}
)
df_siamese_train_pairs["label"].value_counts().rename(
    index={0: "Negative\nPairs", 1: "Positive\nPairs"}
).plot.bar(ax=axes[0], rot=0, color=MAGENTA)
axes[0].tick_params(axis="x", which="major", pad=7)
df_temp.groupby(df_temp.index).sum().plot.bar(ax=axes[1], width=0.6)
fig.tight_layout()

utils_save_plot(plt, REPORT_PATH / f"siamese-{P.name.lower()}-pair-dist.pdf")
```

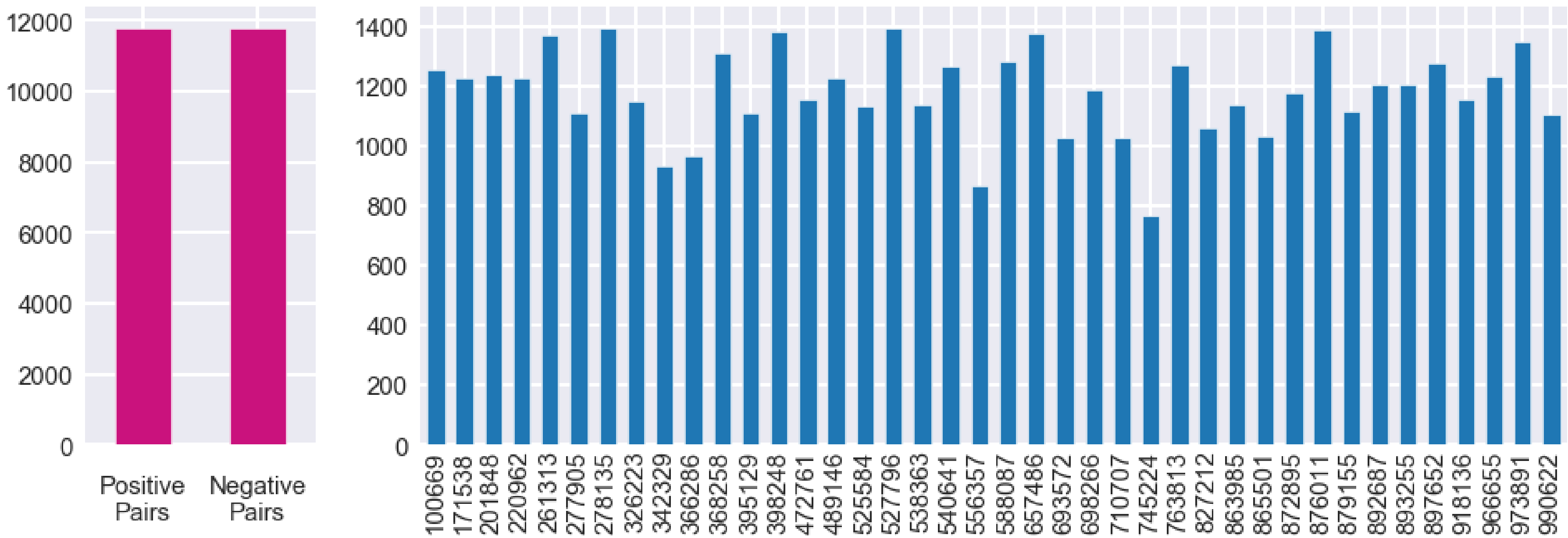
```
DataFrame Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23588 entries, 0 to 23587
Data columns (total 9 columns):
left_X              23588 non-null object
left_subject        23588 non-null object
left_session        23588 non-null object
left_task_type      23588 non-null int64
right_X             23588 non-null object
right_subject       23588 non-null object
right_session       23588 non-null object
right_task_type     23588 non-null int64
label               23588 non-null int32
```

```
dtypes: int32(1), int64(2), object(6)
memory usage: 1.5+ MB

None



Head:
```

	left_X	left_subject	left_session	left_task_type	right_X	right_subject	right_session	right_task_type	l
0	((-0.6109400484616416, -0.2985873893344089, 0....	897652	897652_session_1	4	((0.012159576998761815, -0.36924814907480535, ...	897652	897652_session_3	4	
1	((-0.6852879208892871, -0.9106812206065279, 0....	872895	872895_session_22	6	((0.2728577258370753, 0.1530996859164123, 0.12...	366286	366286_session_8	4	
2	((0.7498410738002906, -0.8684983280458387, 0.5...	698266	698266_session_19	4	((-0.46279022447070506, -0.555800585238564, 0....	220962	220962_session_8	4	
3	((0.10867531040347118, 0.23984956160676224, -0...	865501	865501_session_17	6	((0.21876142696935683, -0.45017171880626056, 0...	865501	865501_session_4	4	
4	((-0.22910759516846307, 0.011331173792316513, ...	990622	990622_session_12	4	((1.9707319594446044, 0.7584409371607767, -0.8...	990622	990622_session_24	4	

```
Any NaN values?

left_X             0
left_subject       0
left_session       0
left_task_type     0
right_X            0
right_subject      0
right_session      0
right_task_type    0
label              0
dtype: int64
```

```
Distribution of Samples per Subjects in training Data
```



3.4 Cache Pairs

In [24]:
```
df_siamese_train_pairs.to_msgpack(OUTPUT_PATH / "df_siamese_train_pairs.msg")
df_siamese_valid_pairs.to_msgpack(OUTPUT_PATH / "df_siamese_valid_pairs.msg")
```

In [25]:
```
# Clean Memory
%reset_selective -f df_
```

4. Siamese Network

4.1 Load cached Pairs

In [26]:
```
df_siamese_train_pairs = pd.read_msgpack(OUTPUT_PATH / "df_siamese_train_pairs.msg")
df_siamese_valid_pairs = pd.read_msgpack(OUTPUT_PATH / "df_siamese_valid_pairs.msg")
```

4.2 Build Model

Distance Function

In [27]:
```
def k_euclidean_dist(t):
    x = t[0]
    y = t[1]
    return K.sqrt(K.sum(K.square(x - y), axis=-1, keepdims=True))
```

Loss Function

In [28]:
```
def k_contrastive_loss(y_true, dist):
    """Contrastive loss from Hadsell-et-al.'06
    http://yann.lecun.com/exdb/publis/pdf/hadsell-chopra-lecun-06.pdf
    """
    margin = P.margin
    return K.mean(y_true * K.square(dist) + (1 - y_true) * K.square(K.maximum(margin - dist, 0)))
```

Sanity check contrastive loss function:

In [29]:
```
def contrastive_loss_test(y_true, dist):
    """Test function above using implementation with numpy instead tensors."""
    margin = P.margin
    return y_true * np.square(dist) + (1 - y_true) * np.square(np.max(margin - dist, 0))
```

In [30]:
```
print("Positive: class=1, distance=0,     loss:", contrastive_loss_test(1, 0))
print("Positive: class=1, distance=0.01,  loss:", contrastive_loss_test(1, 0.01))
print("Positive: class=1, distance=0.3,   loss:", contrastive_loss_test(1, 0.3))
print("Positive: class=1, distance=0.5,   loss:", contrastive_loss_test(1, 0.5))
print("Positive: class=1, distance=1,     loss:", contrastive_loss_test(1, 1))
```

```
Positive: class=1, distance=0,     loss: 0
Positive: class=1, distance=0.01,  loss: 0.0001
Positive: class=1, distance=0.3,   loss: 0.09
Positive: class=1, distance=0.5,   loss: 0.25
Positive: class=1, distance=1,     loss: 1
```

In [31]:
```
print("Negative: class=0, distance=0,     loss:", contrastive_loss_test(0, 0))
print("Negative: class=0, distance=0.01,  loss:", contrastive_loss_test(0, 0.01))
print("Negative: class=0, distance=0.3,   loss:", contrastive_loss_test(0, 0.3))
print("Negative: class=0, distance=0.5,   loss:", contrastive_loss_test(0, 0.5))
print("Negative: class=0, distance=5,     loss:", contrastive_loss_test(0, 1))
```

```
Negative: class=0, distance=0,     loss: 1
Negative: class=0, distance=0.01,  loss: 0.9801
Negative: class=0, distance=0.3,   loss: 0.48999999999999994
Negative: class=0, distance=0.5,   loss: 0.25
Negative: class=0, distance=5,     loss: 0
```

Siamese Model with 2D Filters, as derived from Centeno et al. (2018)

In [32]:
```
def build_model_2d(input_shape, filters):
    """
        Siamese CNN architecture with 3D input and 2D filters
    """
    # Define the tensors for the two input images
    left_inputs = Input(input_shape, name="left_inputs")
    right_inputs = Input(input_shape, name="right_inputs")

    # Convolutional Neural Network
    inputs = Input(input_shape, name="input")
    x = Conv2D(filters[0], (7, 7), padding="same", activation="tanh", name="conv1")(inputs)
    x = MaxPooling2D(pool_size=(2, 2), padding="same", name="mp1")(x)
    x = Conv2D(filters[1], (5, 5), padding="same", activation="tanh", name="conv2")(x)
    x = MaxPooling2D(pool_size=(2, 2), padding="same", name="mp2")(x)
    x = Conv2D(filters[2], (3, 3), padding="same", activation="tanh", name="conv3")(x)
    x = MaxPooling2D(pool_size=(2, 2), padding="same", name="mp3")(x)
    x = Conv2D(filters[3], (3, 3), padding="same", activation="tanh", name="conv4")(x)
    x = MaxPooling2D(pool_size=(2, 2), padding="same", name="mp4")(x)
    x = Flatten(name="flat")(x)

    # Basemodel instance
    basemodel = Model(inputs, x, name="basemodel")

    # using same instance of "basemodel" to share weights between left/right networks
    encoded_l = basemodel(left_inputs)
    encoded_r = basemodel(right_inputs)

    # Add a customized layer to compute the distance between the encodings
    distance_layer = Lambda(k_euclidean_dist, name="distance")([encoded_l, encoded_r])

    # Combine into one net
    siamese_net = Model(inputs=[left_inputs, right_inputs], outputs=distance_layer)

    # return the model
    return siamese_net, basemodel
```

Siamese Model with 1D Filters, similar than Centeno et al. (2018)

In [33]:
```
def build_model_1d(input_shape, filters):
    """
        Model architecture
    """
    # Define the tensors for the two input images
    left_inputs = Input(input_shape, name="left_inputs")
    right_inputs = Input(input_shape, name="right_inputs")

    # Convolutional Neural Network
    inputs = Input(input_shape, name="input")
    x = Conv1D(filters[0], 7, activation="elu", padding="same", name="conv1")(inputs)
    x = MaxPooling1D(pool_size=2, name="mp1")(x)
    x = Conv1D(filters[1], 5, activation="elu", padding="same", name="conv2")(x)
    x = MaxPooling1D(pool_size=2, name="mp2")(x)
    x = Conv1D(filters[2], 3, activation="elu", padding="same", name="conv3")(x)
    x = MaxPooling1D(pool_size=2, name="mp3")(x)
    x = Conv1D(filters[3], 3, activation="elu", padding="same", name="conv4")(x)
    x = MaxPooling1D(pool_size=2, name="mp5")(x)
    x = Flatten(name="flat")(x)

    # Generate the encodings (feature vectors) for the two images
    basemodel = Model(inputs, x, name="basemodel")

    # using same instance of "basemodel" to share weights between left/right networks
    encoded_l = basemodel(left_inputs)
    encoded_r = basemodel(right_inputs)

    # Add a customized layer to compute the absolute difference between the encodings
    distance_layer = Lambda(k_euclidean_dist, name="distance")([encoded_l, encoded_r])

    siamese_net = Model(inputs=[left_inputs, right_inputs], outputs=distance_layer)

    # return the model
    return siamese_net, basemodel
```

Siamese Model with FCN architecture

In [34]:
```
def build_model_fcn(input_shape, filters):
    # Define the tensors for the two input images
    left_inputs = Input(input_shape, name="left_inputs")
    right_inputs = Input(input_shape, name="right_inputs")

    # Convolutional Neural Network
    inputs = Input(input_shape, name="input")
    x = Conv1D(
        filters=filters[0],
        kernel_size=8,
        strides=1,
        activation=None,
        padding="same",
        name="conv1",
    )(inputs)
    x = BatchNormalization()(x)
    x = Activation("relu")(x)
    x = Dropout(0.1, name="drop1")(x)
    x = Conv1D(
        filters=filters[1],
        kernel_size=5,
        strides=1,
        activation=None,
        padding="same",
        name="conv2",
    )(x)
    x = BatchNormalization()(x)
    x = Activation("relu")(x)
    x = Dropout(0.1, name="drop2")(x)
    x = Conv1D(
        filters=filters[2],
        kernel_size=3,
        strides=1,
        activation=None,
        padding="same",
        name="conv3",
    )(x)
    x = BatchNormalization()(x)
    x = Activation("relu")(x)
    x = GlobalAveragePooling1D()(x)
    x = Dense(32, activation="sigmoid", name="dense")(x) # <--- !!!!!!!!!!!!
```

```
    # Basemodel instance
    basemodel = Model(inputs, x, name="basemodel")

    # using same instance of "basemodel" to share weights between left/right networks
    encoded_l = basemodel(left_inputs)
    encoded_r = basemodel(right_inputs)

    # Add a customized layer to compute the distance between the encodings
    distance_layer = Lambda(k_euclidean_dist, name="distance")([encoded_l, encoded_r])

    # Combine into one net
    siamese_net = Model(inputs=[left_inputs, right_inputs], outputs=distance_layer)

    # return the model
    return siamese_net, basemodel
```

In [35]:
```
def get_model(name, window_size, feature_cols, filters):
    print(f"Using Model variant {name}...")
    if name == "1d":
        model, basemodel = build_model_1d((window_size, len(feature_cols)), filters)
    elif name == "2d":
        model, basemodel = build_model_2d((window_size, len(feature_cols), 1), filters)
    elif name == "fcn":
        model, basemodel = build_model_fcn((window_size, len(feature_cols)), filters)
    else:
        raise BaseException("Error: Not a valid model name: {1d, 2d, fcn}")

    return model, basemodel
```

Inspect model architecture:

In [36]:
```
temp_model, temp_basemodel = get_model(P.model_variant, P.window_size, P.feature_cols, P.filters)

temp_basemodel.summary()
temp_model.summary()
```

```
Using Model variant fcn...
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input (InputLayer)           (None, 125, 3)            0         
_________________________________________________________________
conv1 (Conv1D)               (None, 125, 32)           800       
_________________________________________________________________
batch_normalization_1 (Batch (None, 125, 32)           128       
_________________________________________________________________
activation_1 (Activation)    (None, 125, 32)           0         
_________________________________________________________________
drop1 (Dropout)              (None, 125, 32)           0         
_________________________________________________________________
conv2 (Conv1D)               (None, 125, 64)           10304     
_________________________________________________________________
batch_normalization_2 (Batch (None, 125, 64)           256       
_________________________________________________________________
activation_2 (Activation)    (None, 125, 64)           0         
_________________________________________________________________
drop2 (Dropout)              (None, 125, 64)           0         
_________________________________________________________________
conv3 (Conv1D)               (None, 125, 32)           6176      
_________________________________________________________________
batch_normalization_3 (Batch (None, 125, 32)           128       
_________________________________________________________________
activation_3 (Activation)    (None, 125, 32)           0         
_________________________________________________________________
global_average_pooling1d_1 ( (None, 32)                0         
_________________________________________________________________
dense (Dense)                (None, 32)                1056      
=================================================================
Total params: 18,848
Trainable params: 18,592
Non-trainable params: 256
_________________________________________________________________
```

```
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
left_inputs (InputLayer)        (None, 125, 3)       0
__________________________________________________________________________________________________
right_inputs (InputLayer)       (None, 125, 3)       0
__________________________________________________________________________________________________
basemodel (Model)               (None, 32)           18848       left_inputs[0][0]
                                                                 right_inputs[0][0]
__________________________________________________________________________________________________
distance (Lambda)               (None, 1)            0           basemodel[1][0]
                                                                 basemodel[2][0]
==================================================================================================
Total params: 18,848
Trainable params: 18,592
Non-trainable params: 256
__________________________________________________________________________________________________
```

4.3 Prepare Features

In [37]:
```python
def prep_X_y_pair(df):

    X_left = np.stack(list(df["left_X"].values))
    X_right = np.stack(list(df["right_X"].values))

    X = [X_left, X_right]
    y = df["label"].values

    return X, y
```

In [38]:
```
X_train, y_train = prep_X_y_pair(df_siamese_train_pairs)
X_valid, y_valid = prep_X_y_pair(df_siamese_valid_pairs)

# 2D Filter Model needs flat 4th dimension
if P.model_variant == "2d":
    X_train[0] = X_train[0].reshape((*X_train[0].shape, 1))
    X_train[1] = X_train[1].reshape((*X_train[1].shape, 1))
    X_valid[0] = X_valid[0].reshape((*X_valid[0].shape, 1))
    X_valid[1] = X_valid[1].reshape((*X_valid[1].shape, 1))

print(
    f"Training samples:   {y_train.shape[0]}, shape: {X_train[0].shape},"
    + f" class balance: {np.unique(y_train, return_counts=True)}"
)
print(
    f"Validation samples: {y_valid.shape[0]}, shape: {X_valid[0].shape},"
    + f" class balance: {np.unique(y_valid, return_counts=True)}"
)
```

```
Training samples:   23588, shape: (23588, 125, 3), class balance: (array([0, 1]), array([11794, 11794], dtype
=int64))
Validation samples: 5916, shape: (5916, 125, 3), class balance: (array([0, 1]), array([2958, 2958], dtype=int
64))
```

4.4 Search optimal Epoch

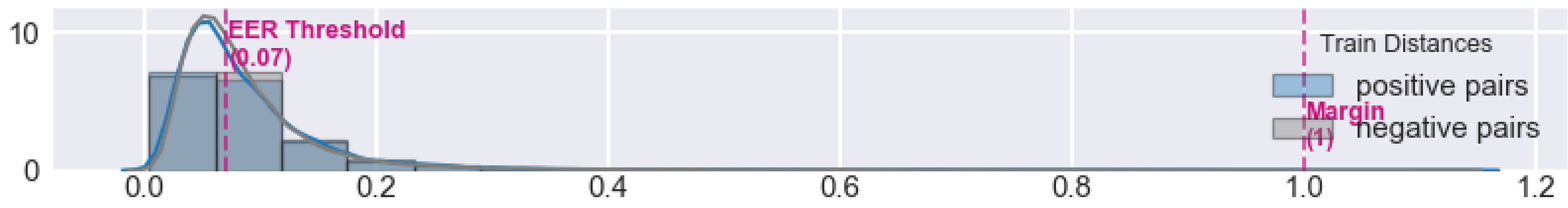
In [39]:
```
class MetricsCallback(Callback):
    """
    Custom Keras Callback function.

    Used to predict and plot distances for positive and negative pairs
    after each n-th epoch, along with some 'classification' metrics.
    'Classification' here means to ability to distinguish between positive
    and negative pairs using a threshold for the distance.

    Arguments:
        payload {tuple}           -- Datasets used for evaluation: (X_valid, y_valid, X_train, y_train)
        epoch_evaluate_freq {int} -- Frequency for evaluation. After every n-th epoch,
                                     the results are evaluated and printed
        save_plots {boolean}      -- Do you want to save plots as PDF? Path is configured via global
                                     parameter REPORT_PATH.
    """

    def __init__(self, payload, epoch_evaluate_freq=1, save_plots=False):

        self.X_valid, self.y_valid, self.X_train, self.y_train = payload
        self.save_plots = save_plots
        self.epoch_evaluate_freq = epoch_evaluate_freq

        # Do we have train and valid set?
        self.sets = []
        if self.X_train:
            self.sets.append([self.X_train, self.y_train, "Train"])
        if self.X_valid:
            self.sets.append([self.X_valid, self.y_valid, "Valid"])

    def on_train_begin(self, logs={}):
        print(32 * "=" + f"[ Initial State ]" + 32 * "=", end="")
        for X, y, desc in self.sets:
            self.evaluate(X, y, logs, desc, -1)

    def on_train_end(self, logs={}):
        print(32 * "=" + f"[ Final State ]" + 32 * "=", end="")
        for X, y, desc in self.sets:
            self.evaluate(X, y, logs, desc, -1)

    def on_epoch_end(self, epoch, logs={}):
```

```
        print(32 * "=" + f"[   Epoch {epoch}   ]" + 32 * "=", end="")
        if epoch % self.epoch_evaluate_freq == 0:  # Evaluate only every n-th epoch
            for X, y, desc in self.sets:
                self.evaluate(X, y, logs, desc, epoch)
        else:
            print(f"\n{ ', '.join([k + ': ' + f'{v:.3f}' for k,v in logs.items()]) }")

    def evaluate(self, X, y, logs, desc, epoch):
        # Predict
        y_score = self.model.predict(X)
        y_score_neg = y_score * -1  # lower distance means closer to positive class

        # Calc Metrics
        roc_val = metrics.roc_auc_score(y, y_score_neg)
        eer_val, thres = utils_eer(y, y_score_neg, True)
        y_pred = np.where(y_score_neg > thres, 1, 0)
        acc_val = metrics.accuracy_score(y, y_pred)
        f1_val = metrics.f1_score(y, y_pred)

        print(
            f"\n{desc.upper()}: roc_auc: {roc_val:.4f}, "
            + f"eer: {eer_val:.4f}, thres: {thres*-1:.4f} => "
            + f"acc: {acc_val:.4f}, f1: {f1_val:.4f}\n"
            + f"{ ', '.join([k + ': ' + f'{v:.3f}' for k,v in logs.items()]) }"
        )

        # Plot distances
        mask = np.where(y == 1, True, False)
        dist_positive = y_score[mask]
        dist_negative = y_score[~mask]
        plt = utils_plot_distance_hist(
            dist_positive, dist_negative, thres * -1, desc=desc, margin=P.margin
        )

        if self.save_plots:
            utils_save_plot(
                plt,
                REPORT_PATH
                / f"siamese-{P.name.lower()}-epoch-{epoch+1}-{desc.lower()}.pdf",
            )

        plt.show()
```

In [40]:
```
def get_optimizer(name, lr=None, decay=None):
    if name == "sgd":
        lr = lr if lr != None else 0.01
        decay = decay if decay != None else 0
        optimizer = SGD(lr=lr, decay=decay)
    elif name == "adam":
        lr = lr if lr != None else 0.001
        decay = decay if decay != None else 0
        optimizer = Adam(lr=lr, decay=decay)
    elif name == "rmsprop":
        lr = lr if lr != None else 0.001
        optimizer = RMSprop(lr=lr)
    else:
        raise BaseException("Error: Not a valid model name: 1d or 2d.")
    return optimizer
```

In [41]:
```
# Select model architecture
model, basemodel = get_model(P.model_variant, P.window_size, P.feature_cols, P.filters)

# Select Optimizer
optimizer = get_optimizer(P.optimizer, P.optimizer_lr)

# Compile
warnings.filterwarnings("ignore")
model.compile(loss=k_contrastive_loss, optimizer=optimizer)

# Train
history = model.fit(
    x=X_train,
    y=y_train,
    batch_size=P.batch_size,
    epochs=P.epochs_max,
    verbose=0,
    validation_data=(X_valid, y_valid),
    callbacks=[MetricsCallback((X_valid, y_valid, X_train, y_train), epoch_evaluate_freq=5, save_plots=True)],
)

print("Training History:")
plt = utils_plot_training_loss(history)
utils_save_plot(
    plt, REPORT_PATH / f"siamese-{P.name.lower()}-epoch-trainloss.pdf"
)
plt.show()
```

```
Using Model variant fcn...
================================[ Initial State ]================================
TRAIN: roc_auc: 0.5053, eer: 0.4963, thres: 0.0708 => acc: 0.5038, f1: 0.5039
```

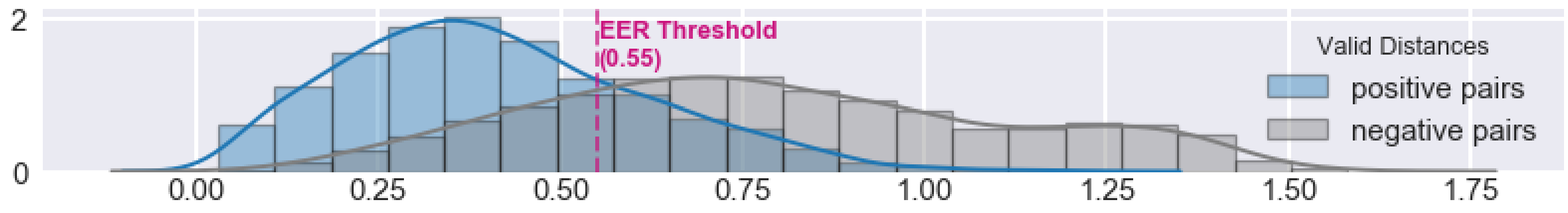


```
VALID: roc_auc: 0.4983, eer: 0.5020, thres: 0.0785 => acc: 0.4978, f1: 0.4979
```

4.5 Check Distances

In [42]:
```
# Predic validation set
dists = model.predict(X_valid)

# Stats
print(f"Mean distance: {dists.mean():.5f}")
print(f"Max distance: {dists.max():.5f}")
print(f"Min distance: {dists.min():.5f}\n")

# Histrogram
print("\nHistogram of Pair Distances:")
eer_val, thres = utils_eer(y_valid, dists, True)
mask = np.where(y_valid == 1, True, False)
dist_positive = dists[mask]
dist_negative = dists[~mask]
plt = utils_plot_distance_hist(dist_positive, dist_negative, thres, "Valid")
plt.show()
```

```
Mean distance: 0.60229
Max distance: 1.58071
Min distance: 0.03007


Histogram of Pair Distances:
```



4.6 Rebuild and train to optimal Epoch

Now, that we know the learning curve, we can rebuild the model and train it until the best Epoch.

Also, we will include the validation data to have more training data.

Note: This also means, that the training metrics are not valid anymore, because we don't have any validation data left to test against...

In [46]:
```
# Concat train & valid data
X_train_valid = [[], []]
X_train_valid[0] = np.vstack([X_train[0], X_valid[0]])
X_train_valid[1] = np.vstack([X_train[1], X_valid[1]])
y_train_valid = np.hstack([y_train, y_valid])

# Select model architecture
model, basemodel = get_model(P.model_variant, P.window_size, P.feature_cols, P.filters)

# Select Optimizer
optimizer = get_optimizer(P.optimizer, P.optimizer_lr)

# Compile
model.compile(loss=k_contrastive_loss, optimizer=optimizer)

# Train
history = model.fit(
    x=X_train_valid,
    y=y_train_valid,
    batch_size=P.batch_size,
    epochs=P.epochs_best,
    verbose=0,
    callbacks=[MetricsCallback((None, None, X_train, y_train), epoch_evaluate_freq=10, save_plots=False)],
)
```

```
Using Model variant fcn...

C:\Users\ubo8fe\.conda\envs\continauth\lib\site-packages\numpy\lib\type_check.py:546: DeprecationWarning: np.
asscalar(a) is deprecated since NumPy v1.16, use a.item() instead
  'a.item() instead', DeprecationWarning, stacklevel=1)

================================[ Initial State ]=================================
TRAIN: roc_auc: 0.4940, eer: 0.5113, thres: 0.0721 => acc: 0.4887, f1: 0.4887
```

4.7 Cache model

In [47]:
```
model.save(str((OUTPUT_PATH / f"{P.name}_model.h5").resolve()))
```

In [48]:
```
# Clean Memory
%reset_selective -f df_
%reset_selective -f X_
%reset_selective -f y_
```

5. Visualize Deep Features

5.1 Load cached Data

In [49]:
```
df_siamese_valid = pd.read_msgpack(OUTPUT_PATH / "df_siamese_valid.msg")
df_siamese_train = pd.read_msgpack(OUTPUT_PATH / "df_siamese_train.msg")

df_ocsvm_train_valid = pd.read_msgpack(OUTPUT_PATH / "df_ocsvm_train_valid.msg")
```

5.2 Extract CNN from Siamese Model

I do this by redirecting inputs and outputs.

However, the network still needs a pair as input (I wasn't able to change this). This slows down a little bit the prediction (as the input is predicted twice), but doesn't change the results.

In [50]:
```
def load_deep_feature_model(model_path):
    # Copy of function from above. It's just more convenient for partially
    # executing the notebook.
    def k_contrastive_loss(y_true, dist):
        """Contrastive loss from Hadsell-et-al.'06
        http://yann.lecun.com/exdb/publis/pdf/hadsell-chopra-lecun-06.pdf
        """
        margin = P.margin
        return K.mean(
            y_true * K.square(dist)
            + (1 - y_true) * K.square(K.maximum(margin - dist, 0))
        )

    # Load Trained Siamese Network
    model = load_model(
        str(model_path.resolve()),
        custom_objects={"k_contrastive_loss": k_contrastive_loss},
    )

    # Extract one of the child networks
    deep_feature_model = Model(
        inputs=model.get_input_at(0),  # get_layer("left_inputs").input,
        outputs=model.get_layer("basemodel").get_output_at(1),
    )

    return deep_feature_model
```

In [51]:
```
deep_feature_model = load_deep_feature_model(OUTPUT_PATH / f"{P.name}_model.h5")
deep_feature_model.summary()
```

```
C:\Users\ubo8fe\.conda\envs\continauth\lib\site-packages\numpy\lib\type_check.py:546: DeprecationWarning: np.
asscalar(a) is deprecated since NumPy v1.16, use a.item() instead
  'a.item() instead', DeprecationWarning, stacklevel=1)
C:\Users\ubo8fe\.conda\envs\continauth\lib\site-packages\keras\engine\saving.py:251: DeprecationWarning: The
truth value of an empty array is ambiguous. Returning False, but in future this will result in an error. Use
`array.size > 0` to check that an array is not empty.
  if weight_names:

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
left_inputs (InputLayer)     (None, 125, 3)            0
_________________________________________________________________
basemodel (Model)            (None, 32)                18848
=================================================================
Total params: 18,848
Trainable params: 18,592
Non-trainable params: 256
_________________________________________________________________
```

5.3 Test Generation of Deep Features

In [52]:
```
def prep_X_y_single(df):
    X = np.stack(list(df["X"].values))
    y = df["label"].values
    return X, y
```

In [53]:
```
def transform_to_sample_by_subject(df):
    sample_by_subject = []
    df["label"] = 1
    for subj in df["subject"].unique():
        df_subj = df[df["subject"] == subj]
        X_sub, y_sub = prep_X_y_single(df_subj)
        sample_by_subject.append((X_sub, y_sub, subj))
    return sample_by_subject
```

Select subset (for plotting) and transform features

In [54]:
```
# Concat Valid & Train (both were used for last Training)
df_train_temp = pd.concat([df_siamese_valid, df_siamese_train])
df_test_temp = df_ocsvm_train_valid

# Select data from 20 subjects of the TRAINING SET
random.seed(SEED)
ten_subjects = random.sample(df_train_temp["subject"].unique().tolist(), 20)
df_train_temp = df_train_temp[df_train_temp["subject"].isin(ten_subjects)].copy()
df_train_temp = df_train_temp.groupby("subject").apply(lambda x: x.sample(n=300, random_state=SEED))  # Plot
only subset of samples

# Select data from 10 subjects of the TEST SET (not included in training)
random.seed(SEED)
ten_subjects = random.sample(df_test_temp["subject"].unique().tolist(), 10)
df_test_temp = df_test_temp[df_ocsvm_train_valid["subject"].isin(ten_subjects)].copy()
df_test_temp = df_test_temp.groupby("subject").apply(lambda x: x.sample(n=300, random_state=SEED))  # Plot
only subset of samples

# Transform Samples
samples_train = transform_to_sample_by_subject(df_train_temp)
samples_test = transform_to_sample_by_subject(df_test_temp)

print(f"First subject: {samples_train[0][2]}")
print(f"y shape: {samples_train[0][1].shape}")
print(f"X shape: {samples_train[0][0].shape}")
```

```
First subject: 201848
y shape: (300,)
X shape: (300, 125, 3)
```

Predict Deep Features

In [55]:
```
deep_features_train = None
for X, y, subj in samples_train:
    if P.model_variant == "2d":
        X = X.reshape((*X.shape, 1))
    pred = deep_feature_model.predict([X, X])
    df_features = pd.DataFrame(pred)
    df_features["subject"] = subj
    deep_features_train = pd.concat([deep_features_train, df_features])

deep_features_test = None
for X, y, subj in samples_test:
    if P.model_variant == "2d":
        X = X.reshape((*X.shape, 1))
    pred = deep_feature_model.predict([X, X])
    df_features = pd.DataFrame(pred)
    df_features["subject"] = subj
    deep_features_test = pd.concat([deep_features_test, df_features])

display(deep_features_train.head(3))
display(deep_features_test.head(3))
```

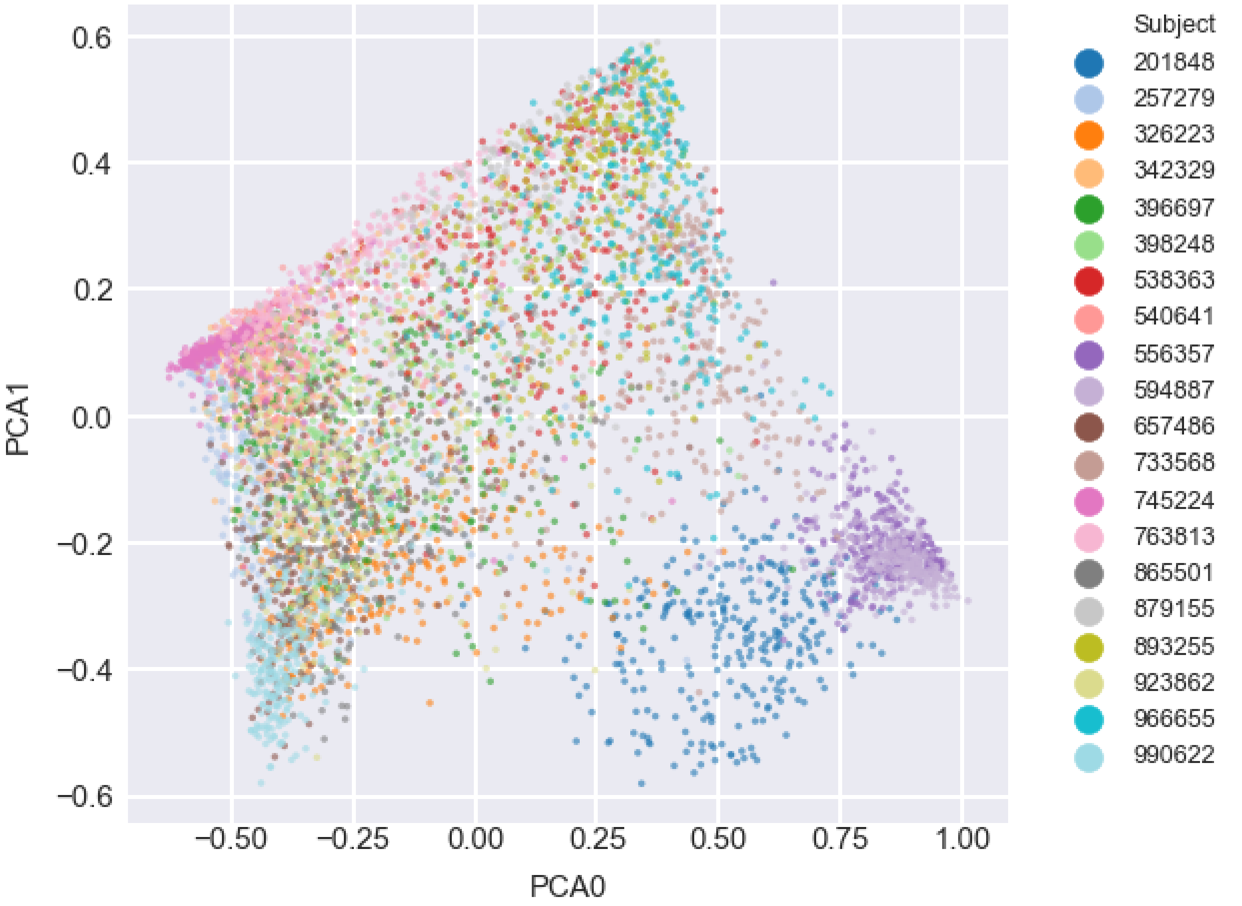
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	
0	0.532730	0.601433	0.571256	0.679295	0.328800	0.522838	0.307816	0.113038	0.411330	0.680915	0.751487	0.556759	0.261712	0.334964	0.33
1	0.534855	0.609086	0.554191	0.655128	0.338823	0.502882	0.306396	0.105658	0.410040	0.664141	0.758147	0.891228	0.239795	0.302278	0.34
2	0.534626	0.603354	0.541992	0.621395	0.346483	0.490232	0.314961	0.122119	0.414695	0.655088	0.760665	0.891732	0.254550	0.276144	0.35

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	
0	0.630102	0.389935	0.600983	0.995539	0.324329	0.344570	0.284509	0.476761	0.366598	0.741183	0.905276	0.809473	0.244208	0.984357	0.38
1	0.610046	0.408789	0.624025	0.999667	0.327028	0.285955	0.261226	0.279809	0.314211	0.759063	0.926064	0.710405	0.144351	0.999541	0.38
2	0.617656	0.424365	0.588124	0.988008	0.330435	0.366511	0.289660	0.425268	0.378557	0.725200	0.888119	0.811422	0.253652	0.955892	0.38

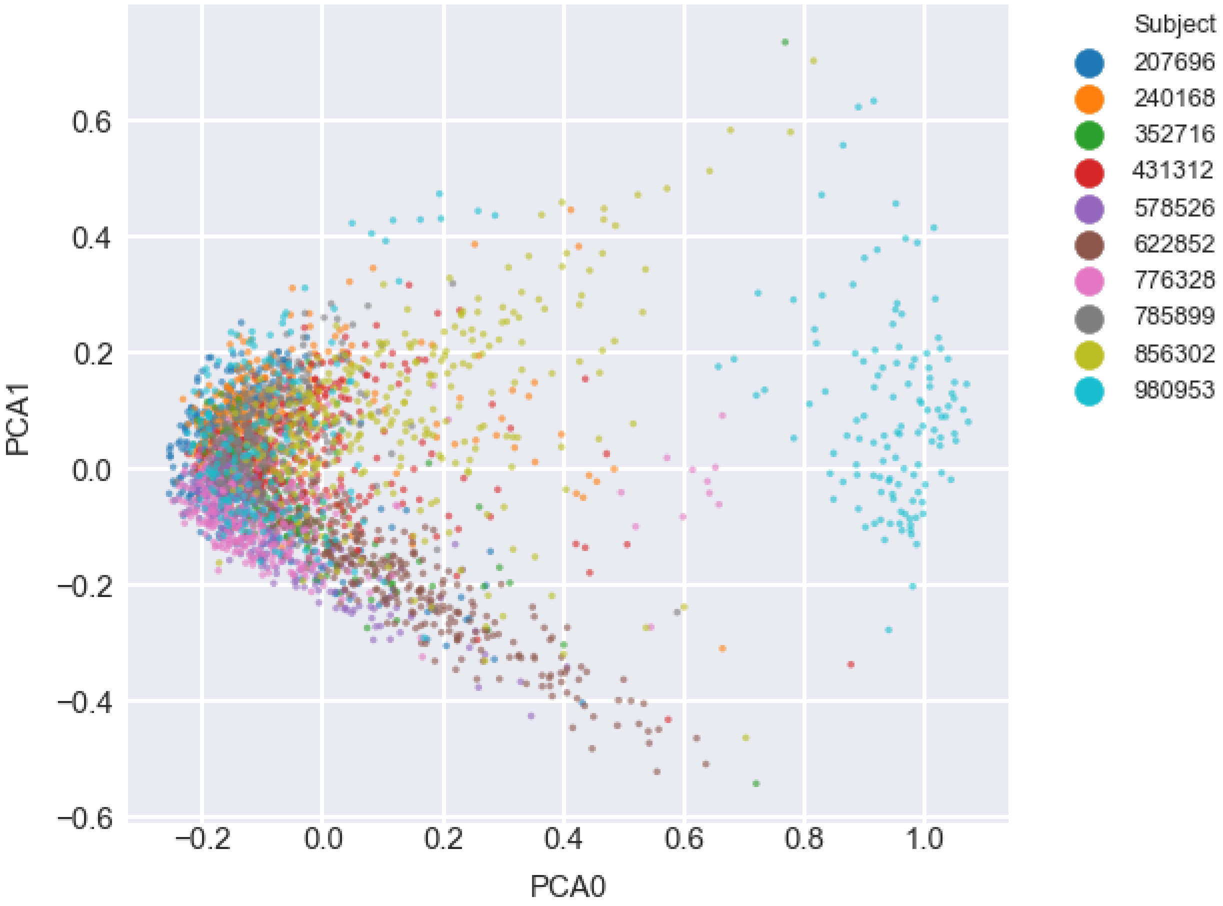
5.4 Visualize in 2D using PCA

In [56]:
```
def plot_pca(df):
    # PCA
    pca = PCA(n_components=2)
    deep_transformed = pca.fit_transform(df.drop(columns=["subject"]).values)

    # Create df with data needed for chart only
    df_viz = df.copy()
    df_viz["PCA0"] = deep_transformed[:, 0]
    df_viz["PCA1"] = deep_transformed[:, 1]
    df_viz.drop(
        columns=[c for c in df_viz.columns if c not in ["PCA0", "PCA1", "subject"]]
    )

    # Generate color index for every subject
    df_viz["Subject"] = pd.Categorical(df_viz["subject"])
    df_viz["colors"] = df_viz["Subject"].cat.codes

    if len(df_viz["Subject"].unique()) <= 10:
        pal = sns.color_palette("tab10")
    else:
        pal = sns.color_palette("tab20")

    # Actual plot
    fig = plt.figure(figsize=(5.473 / 1.5, 5.473 / 2), dpi=180)
    sns.scatterplot(
        x="PCA0",
        y="PCA1",
        data=df_viz,
        hue="Subject",
        legend="full",
        palette=pal,
        s=2,
        linewidth=0,
        alpha=0.6,
    )
    plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0, fontsize=5)
    fig.tight_layout()
    return plt
```

In [57]:
```
plot_pca(deep_features_train)
utils_save_plot(plt, REPORT_PATH / f"siamese-{P.name.lower()}-pca-train.pdf")
```



In [58]:
```
plot_pca(deep_features_test)
utils_save_plot(plt, REPORT_PATH / f"siamese-{P.name.lower()}-pca-test.pdf")
```



In [59]:
```
### Cleanup memory
%reset_selective -f df_
%reset_selective -f X_
%reset_selective -f y_
%reset_selective -f pca
```

6. OCSVM

6.1 Load cached Data

In [60]:
```
df_ocsvm_train_valid = pd.read_msgpack(OUTPUT_PATH / "df_ocsvm_train_valid.msg")
df_ocsvm_train_valid.head()
```

Out[60]:

	X	subject	session	task_type
0	((1.3978850635805664, 6.634745158553127, 8.873...	207696	207696_session_11	2
1	((0.8989105212499999, 7.4393458625, 5.20084218...	207696	207696_session_11	2
2	((-0.8528512094444445, 5.462304877777777, 7.74...	207696	207696_session_11	2
3	((-2.062305483175016, 4.1703999289186555, 7.23...	207696	207696_session_11	2
4	((-0.9964742910047201, 4.9818725305168, 8.2125...	207696	207696_session_11	2

6.2 Load trained Siamese Model

Helper methods to load model:

In [61]:
```
def load_deep_feature_model(model_path):
    warnings.filterwarnings("ignore")  # Silence depr. warnings

    # Copy of function from above. It's just more convenient for partially executing the notebook.
    def k_contrastive_loss(y_true, dist):
        """Contrastive loss from Hadsell-et-al.'06
        http://yann.lecun.com/exdb/publis/pdf/hadsell-chopra-lecun-06.pdf
        """
        margin = P.margin
        return K.mean(
            y_true * K.square(dist)
            + (1 - y_true) * K.square(K.maximum(margin - dist, 0))
        )

    # Load Trained Siamese Network
    model = load_model(
        str(model_path.resolve()),
        custom_objects={"k_contrastive_loss": k_contrastive_loss},
    )

    # Extract one of the child networks
    deep_feature_model = Model(
        inputs=model.get_input_at(0),  # get_layer("left_inputs").input,
        outputs=model.get_layer("basemodel").get_output_at(1),
    )

    return deep_feature_model
```

Sanity Check:

6.3 Search for Parameters

In [62]:
```
df_ocsvm_train_valid.head()
```

Out[62]:

	X	subject	session	task_type
0	((1.3978850635805664, 6.634745158553127, 8.873...	207696	207696_session_11	2
1	((0.8989105212499999, 7.4393458625, 5.20084218...	207696	207696_session_11	2
2	((-0.8528512094444445, 5.462304877777777, 7.74...	207696	207696_session_11	2
3	((-2.062305483175016, 4.1703999289186555, 7.23...	207696	207696_session_11	2
4	((-0.9964742910047201, 4.9818725305168, 8.2125...	207696	207696_session_11	2

In [63]:
```
param_dist = {"gamma": np.logspace(-3, 3), "nu": np.linspace(0.0001, 0.3)}

# Load Siamese CNN Model
deep_feature_model = load_deep_feature_model(OUTPUT_PATH / f"{P.name}_model.h5")

df_results = None  # Will be filled with randomsearch scores

for run in tqdm(range(3)):
    for df_cv_scenarios, owner, impostors in tqdm(
        utils_generate_cv_scenarios(
            df_ocsvm_train_valid,
            samples_per_subject_train=P.samples_per_subject_train,
            samples_per_subject_test=P.samples_per_subject_test,
            seed=SEED + run,
            scaler=P.scaler,
            scaler_global=P.scaler_global,
            scaler_scope=P.scaler_scope,
            deep_model=deep_feature_model,
            model_variant=P.model_variant,
            feature_cols=P.feature_cols,
        ),
        desc="Owner",
        total=df_ocsvm_train_valid["subject"].nunique(),
        leave=False,
    ):

        X = np.array(df_cv_scenarios["X"].values.tolist())
        y = df_cv_scenarios["label"].values

        train_valid_cv = utils_create_cv_splits(df_cv_scenarios["mask"].values, SEED)

        model = OneClassSVM(kernel="rbf")

        warnings.filterwarnings("ignore")
        random_search = RandomizedSearchCV(
            model,
            param_distributions=param_dist,
            cv=train_valid_cv,
            n_iter=80,
            n_jobs=CORES,
            refit=False,
```

```
            scoring={"eer": utils_eer_scorer, "accuracy": "accuracy"},
            verbose=0,
            return_train_score=False,
            iid=False,
            error_score=np.nan,
            random_state=SEED,
        )

        random_search.fit(X, y)

        df_report = utils_cv_report(random_search, owner, impostors)
        df_report["run"] = run
        df_results = pd.concat([df_results, df_report], sort=False)

df_results.to_csv(OUTPUT_PATH / f"{P.name}_random_search_results.csv", index=False)
```

```
HBox(children=(IntProgress(value=0, max=3), HTML(value='')))

HBox(children=(IntProgress(value=0, description='Owner', max=10, style=ProgressStyle(description_width='initi
a…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…
```

```
HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='Owner', max=10, style=ProgressStyle(description_width='initi
a…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='Owner', max=10, style=ProgressStyle(description_width='initi
a…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…
```

```
HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…
```

6.4 Inspect Search Results

Raw Results & Stats:

In [64]:
```
df_results = pd.read_csv(OUTPUT_PATH / f"{P.name}_random_search_results.csv")
print("Best results for each owner:")

display(
    df_results[df_results["rank_test_eer"] <= 1][
        [
            "owner",
            "param_nu",
            "param_gamma",
            "rank_test_eer",
            "mean_test_eer",
            "std_test_eer",
            "mean_test_accuracy",
            "std_test_accuracy",
        ]
    ].sort_values("mean_test_eer").head(10)
)

print("\n\n\nMost relevant statistics:")
display(
    df_results[df_results["rank_test_eer"] <= 1][
        [
            "mean_fit_time",
            "param_nu",
            "param_gamma",
            "mean_test_accuracy",
            "std_test_accuracy",
            "mean_test_eer",
            "std_test_eer",
        ]
    ].describe()
)
```

```
Best results for each owner:
```

	owner	param_nu	param_gamma	rank_test_eer	mean_test_eer	std_test_eer	mean_test_accuracy	std_test_accuracy
446	622852	0.177592	6.250552	1.0	0.144939	0.088237	0.875661	0.074686
1406	622852	0.177592	6.250552	1.0	0.207389	0.082763	0.812169	0.078923
2126	207696	0.177592	6.250552	1.0	0.234057	0.135951	0.797619	0.122567

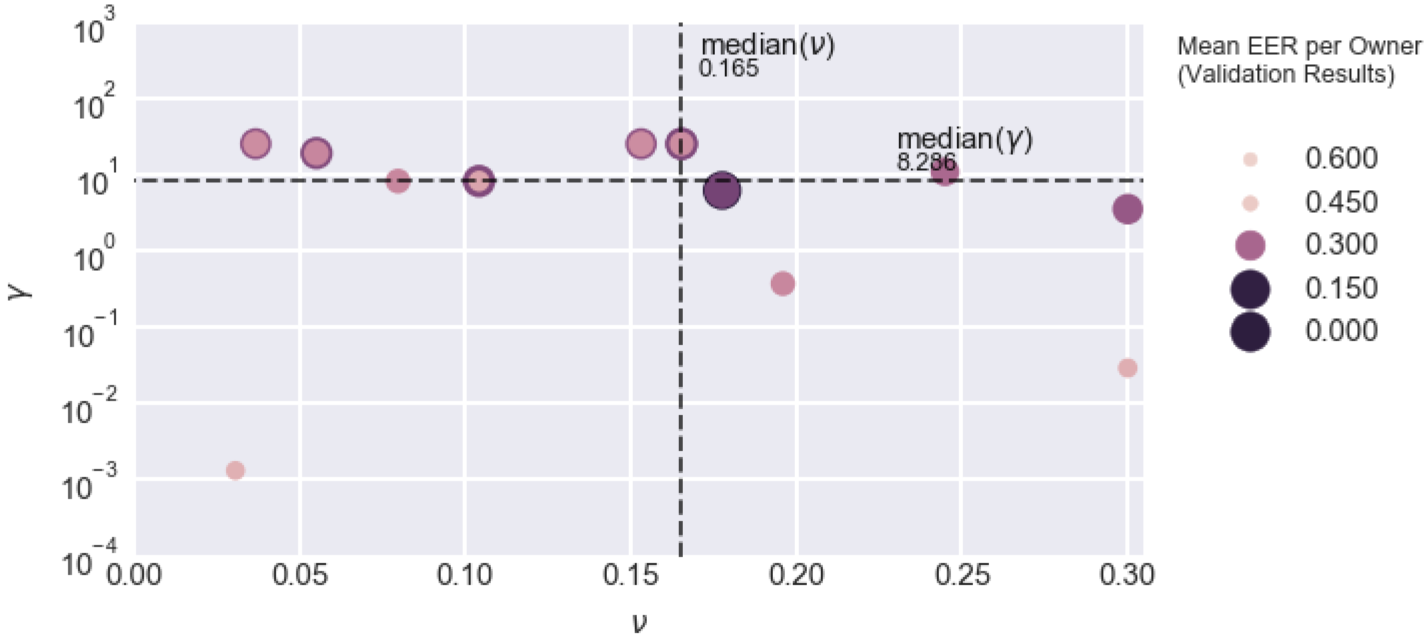
	owner	param_nu	param_gamma	rank_test_eer	mean_test_eer	std_test_eer	mean_test_accuracy	std_test_accuracy
1806	785899	0.177592	6.250552	1.0	0.234362	0.096577	0.801587	0.088020
2206	622852	0.177592	6.250552	1.0	0.234714	0.053715	0.806878	0.068452
1246	785899	0.177592	6.250552	1.0	0.238865	0.076039	0.792328	0.069441
1466	578526	0.165351	25.595479	1.0	0.245940	0.046283	0.773810	0.049880
645	785899	0.104147	8.286428	1.0	0.248065	0.086426	0.785714	0.084366
1056	207696	0.055184	19.306977	1.0	0.251459	0.094805	0.779101	0.097220
14	352716	0.153110	25.595479	1.0	0.265119	0.029941	0.764550	0.052578

```
Most relevant statistics:
```

	mean_fit_time	param_nu	param_gamma	mean_test_accuracy	std_test_accuracy	mean_test_eer	std_test_eer
count	36.000000	36.000000	36.000000	36.000000	36.000000	36.000000	36.000000
mean	0.000386	0.155830	12.963256	0.708848	0.076972	0.318534	0.068432
std	0.000732	0.083835	9.565549	0.071990	0.021661	0.069539	0.027915
min	0.000000	0.030702	0.001326	0.552910	0.041239	0.144939	0.027174
25%	0.000000	0.073545	6.250552	0.660714	0.060098	0.261704	0.050551
50%	0.000000	0.165351	8.286428	0.703704	0.078745	0.348469	0.071402
75%	0.000000	0.177592	25.595479	0.766865	0.085280	0.362760	0.088247
max	0.001739	0.300000	25.595479	0.875661	0.122567	0.461055	0.135951

Plot parameters of top n of 30 results for every Owner:

In [65]:
```
utils_plot_randomsearch_results(df_results, 1)
utils_save_plot(plt, REPORT_PATH / f"siamese-{P.name.lower()}-parameters.pdf")
```



7. Testing

7.1 Load cached Data

During testing, a split with different users than used for hyperparameter optimization is used:

In [69]:
```
df_ocsvm_train_test = pd.read_msgpack(OUTPUT_PATH / "df_ocsvm_train_test.msg")
```

7.2 Evaluate Authentication Performance

- Using Testing Split, Scenario Cross Validation, and multiple runs to lower impact of random session/sample selection.

In [70]:
```
# Load Siamese CNN Model
deep_feature_model = load_deep_feature_model(OUTPUT_PATH / f"{P.name}_model.h5")

df_results = None  # Will be filled with cv scores
for i in tqdm(range(5), desc="Run", leave=False):  # Run whole test 5 times
    for df_cv_scenarios, owner, impostors in tqdm(
        utils_generate_cv_scenarios(
            df_ocsvm_train_test,
            samples_per_subject_train=P.samples_per_subject_train,
            samples_per_subject_test=P.samples_per_subject_test,
            seed=SEED,
            scaler=P.scaler,
            scaler_global=P.scaler_global,
            scaler_scope=P.scaler_scope,
            deep_model=deep_feature_model,
            model_variant=P.model_variant,
            feature_cols=P.feature_cols,
        ),
        desc="Owner",
        total=df_ocsvm_train_test["subject"].nunique(),
        leave=False,
    ):

        X = np.array(df_cv_scenarios["X"].values.tolist())
        y = df_cv_scenarios["label"].values

        train_test_cv = utils_create_cv_splits(df_cv_scenarios["mask"].values, SEED)

        model = OneClassSVM(kernel="rbf", nu=P.ocsvm_nu, gamma=P.ocsvm_gamma)

        warnings.filterwarnings("ignore")
        scores = cross_validate(
            model,
            X,
            y,
            cv=train_test_cv,
            scoring={"eer": utils_eer_scorer, "accuracy": "accuracy"},
            n_jobs=CORES,
            verbose=0,
            return_train_score=True,
        )
```

```
        df_score = pd.DataFrame(scores)
        df_score["owner"] = owner
        df_score["train_eer"] = df_score["train_eer"].abs()  # Revert scorer's signflip
        df_score["test_eer"] = df_score["test_eer"].abs()
        df_results = pd.concat([df_results, df_score], axis=0)

df_results.to_csv(OUTPUT_PATH / f"{P.name}_test_results.csv", index=False)
df_results.head()
```

```
HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…
```

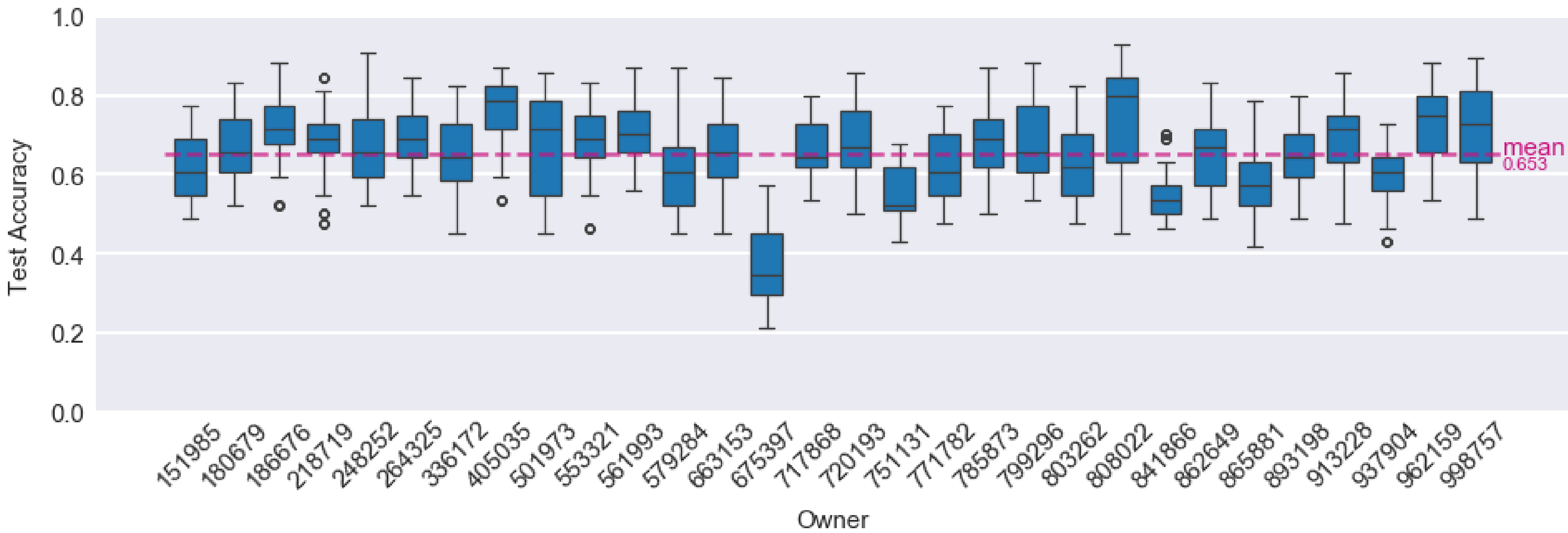
Load Results from "EER & Accuracy" evaluation & prepare for plotting:

In [71]:
```
df_results = pd.read_csv(OUTPUT_PATH / f"{P.name}_test_results.csv")
df_plot = df_results.rename(
    columns={"test_accuracy": "Test Accuracy", "test_eer": "Test EER", "owner": "Owner"}
).astype({"Owner": str})
```

Plot Distribution of Accuracy per subject:

In [72]:
```
fig = utils_plot_acc_eer_dist(df_plot, "Test Accuracy")
utils_save_plot(plt, REPORT_PATH / f"siamese-{P.name.lower()}-acc.pdf")
```

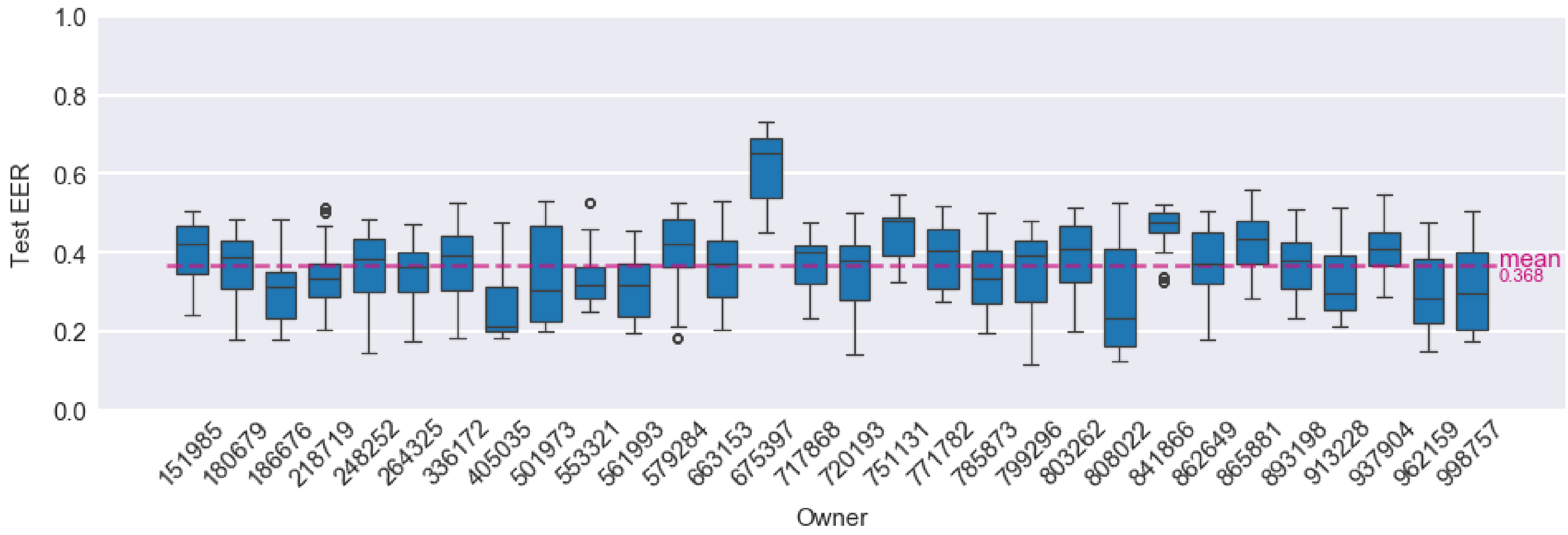
```
Overall mean: 0.6530
```



Plot Distribution of EER per subject:

In [73]:
```
fig = utils_plot_acc_eer_dist(df_plot, "Test EER")
utils_save_plot(plt, REPORT_PATH / f"siamese-{P.name.lower()}-eer.pdf")
```

```
Overall mean: 0.3684
```



7.3 Evaluate increasing Training Set Size (Training Delay)

In [74]:
```
training_set_sizes = [1, 2, 3, 4, 10, 30, 60, 90, 125, 175, 250, 375]  # In samples

deep_feature_model = load_deep_feature_model(OUTPUT_PATH / f"{P.name}_model.h5")

df_results = None  # Will be filled with cv scores
for i in tqdm(range(5), desc="Run", leave=False):  # Run whole test 5 times
    for n_train_samples in tqdm(training_set_sizes, desc="Train Size", leave=False):
        for df_cv_scenarios, owner, impostors in tqdm(
            utils_generate_cv_scenarios(
                df_ocsvm_train_test,
                samples_per_subject_train=P.samples_per_subject_train,
                samples_per_subject_test=P.samples_per_subject_test,
                limit_train_samples=n_train_samples,  # samples overall
                seed=SEED + i,
                scaler=P.scaler,
                scaler_global=P.scaler_global,
                scaler_scope=P.scaler_scope,
                deep_model=deep_feature_model,
                model_variant=P.model_variant,
                feature_cols=P.feature_cols,
            ),
            desc="Owner",
            total=df_ocsvm_train_test["subject"].nunique(),
            leave=False,
        ):
            X = np.array(df_cv_scenarios["X"].values.tolist())
            y = df_cv_scenarios["label"].values

            train_test_cv = utils_create_cv_splits(df_cv_scenarios["mask"].values, SEED)

            model = OneClassSVM(kernel="rbf", nu=P.ocsvm_nu, gamma=P.ocsvm_gamma)

            warnings.filterwarnings("ignore")
            scores = cross_validate(
                model,
                X,
                y,
                cv=train_test_cv,
                scoring={"eer": utils_eer_scorer},
                n_jobs=CORES,
                verbose=0,
```

```
                    return_train_score=True,
                )
                df_score = pd.DataFrame(scores)
                df_score["owner"] = owner
                df_score["train_samples"] = n_train_samples
                df_score["train_eer"] = df_score[
                    "train_eer"
                ].abs()  # Revert scorer's signflip
                df_score["test_eer"] = df_score["test_eer"].abs()
                df_results = pd.concat([df_results, df_score], axis=0)

df_results.to_csv(OUTPUT_PATH / f"{P.name}_train_delay_results.csv", index=False)
df_results.head()
```

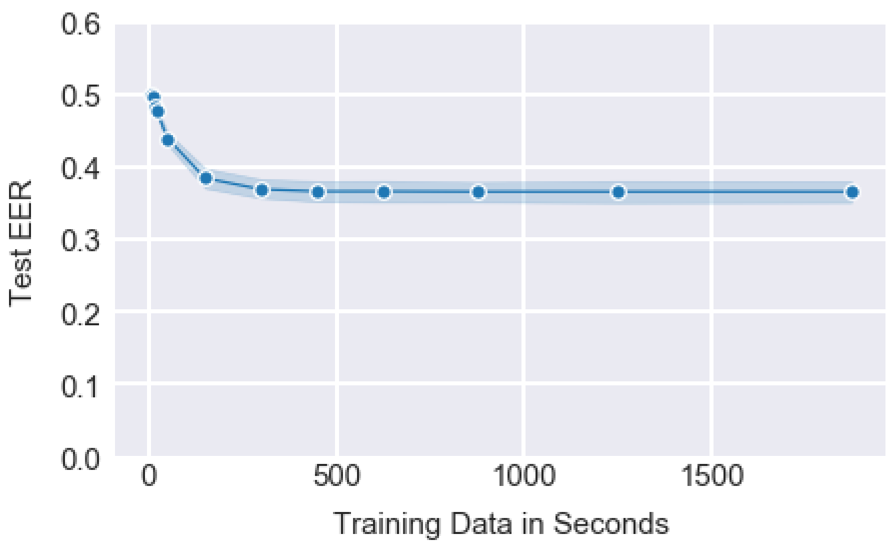
```
HBox(children=(IntProgress(value=0, description='Run', max=5, style=ProgressStyle(description_width='initia
l')…

HBox(children=(IntProgress(value=0, description='Train Size', max=12, style=ProgressStyle(description_width
='i…

HBox(children=(IntProgress(value=0, description='Owner', max=30, style=ProgressStyle(description_width='initi
a…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…
```

Load Results from "Training set size" evaluation & prepare for plotting:

In [75]:
```
df_results = pd.read_csv(OUTPUT_PATH / f"{P.name}_train_delay_results.csv")
df_plot = (
    df_results[["test_eer", "owner", "train_samples"]]
    .groupby(["owner", "train_samples"], as_index=False)
    .mean()
    .astype({"owner": "category"})
    .rename(
        columns={
            "test_eer": "Test EER",
            "owner": "Owner",
        }
    )
)
df_plot["Training Data in Seconds"] = df_plot["train_samples"] * P.window_size / P.frequency
```

Plot EER with increasing number of training samples:

In [76]:
```
utils_plot_training_delay(df_plot)
utils_save_plot(plt, REPORT_PATH / f"siamese-{P.name.lower()}-train-size.pdf")
```



7.4 Evaluate increasing Test Set Sizes (Detection Delay)

In [77]:
```
# Load Siamese CNN Model
deep_feature_model = load_deep_feature_model(OUTPUT_PATH / f"{P.name}_model.h5")

df_results = None  # Will be filled with cv scores
for i in tqdm(range(50), desc="Run", leave=False):  # Run whole test 5 times
    for df_cv_scenarios, owner, impostors in tqdm(
        utils_generate_cv_scenarios(
            df_ocsvm_train_test,
            samples_per_subject_train=P.samples_per_subject_train,
            samples_per_subject_test=P.samples_per_subject_test,
            limit_test_samples=1,  # Samples overall
            seed=SEED + i,
            scaler=P.scaler,
            scaler_global=P.scaler_global,
            scaler_scope=P.scaler_scope,
            deep_model=deep_feature_model,
            model_variant=P.model_variant,
            feature_cols=P.feature_cols,
        ),
        desc="Owner",
        total=df_ocsvm_train_test["subject"].nunique(),
        leave=False,
    ):
        X = np.array(df_cv_scenarios["X"].values.tolist())
        y = df_cv_scenarios["label"].values

        train_test_cv = utils_create_cv_splits(df_cv_scenarios["mask"].values, SEED)

        model = OneClassSVM(kernel="rbf", nu=P.ocsvm_nu, gamma=P.ocsvm_gamma)

        warnings.filterwarnings("ignore")
        scores = cross_validate(
            model,
            X,
            y,
            cv=train_test_cv,
            scoring={"eer": utils_eer_scorer},
            n_jobs=CORES,
            verbose=0,
            return_train_score=True,
        )
```

```
        df_score = pd.DataFrame(scores)
        df_score["owner"] = owner
        df_score["run"] = i
        df_score["train_eer"] = df_score["train_eer"].abs()  # Revert scorer's signflip
        df_score["test_eer"] = df_score["test_eer"].abs()
        df_results = pd.concat([df_results, df_score], axis=0)

df_results.to_csv(OUTPUT_PATH / f"{P.name}_detect_delay_results.csv", index=False)
df_results.head()
```

```
HBox(children=(IntProgress(value=0, description='Run', max=50, style=ProgressStyle(description_width='initia
l'…

HBox(children=(IntProgress(value=0, description='Owner', max=30, style=ProgressStyle(description_width='initi
a…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…

HBox(children=(IntProgress(value=0, description='subjects', max=1, style=ProgressStyle(description_width='ini
t…
```

Load Results from "Detection Delay" evaluation & prepare for plotting:

In [78]:
```
df_results = pd.read_csv(OUTPUT_PATH / f"{P.name}_detect_delay_results.csv")
df_results["owner"] = df_results["owner"].astype(str)
df_plot = df_results.copy()
```