ASL Classification for Augmented Reality Interactive Learning

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Business Problem

In 2017, researchers at Georgia Tech university released the app PopSign! Using dynamic image classification game where users use ASL signs to control a cannon and pop the bubbles. The app tackles the rich idea of gamifying the learning process for learning ASL, targeting parents and relatives of deaf individuals. Unfortunately, there hasn't been enough development with the concept in comparison to the leaps in computer vision technology we've seen in AI research.

Six years later, Google releases their 'Isolated Sign Language Recognition' Dataset as part of a Kaggle competition. So I will help enhace PopSign's educational games.

Goals

- Accurately classify ASL sign from video footage
- Optimize lightweighted-ness of our model for scalability and ease of use for a phone app
- Optimize *recall* for more common words
- Demonstrate the proof of concept for fututre testing and Deployment

Data Understanding

Google's Isolated Sign Language Recognition Dataset (54.43 GB):

- 94k short clips (about 7-40 frames) of isolated ASL signs
- 250 unique signs represented
- 21 unique signers

The video footage has been preprocessed through MediaPipe's Holistic Solution model, mapping points (landmarks) on the face, hands and body as x-y-z coordinates in the frame. Every clip comes in a .parquet file, where each row contains:

- *row_id* : unique id string combining the other features
- *frame* : frame number
- *type* : the body part this landmark is part of (face, pose, right_hand, left_hand)
- *landmark_index* : id of the landmark within it's *type*
- *x*, *y*, *z* : coordinate positions normalized [0,1], although the Holistic model has not been optimized to accurately map depth *z*

Finally, for each frame we consistently have:

- Pose landmarks: 33 rows
- Right hand landmarks: 21 rows
- Left hand landmarks: 21 rows

imports

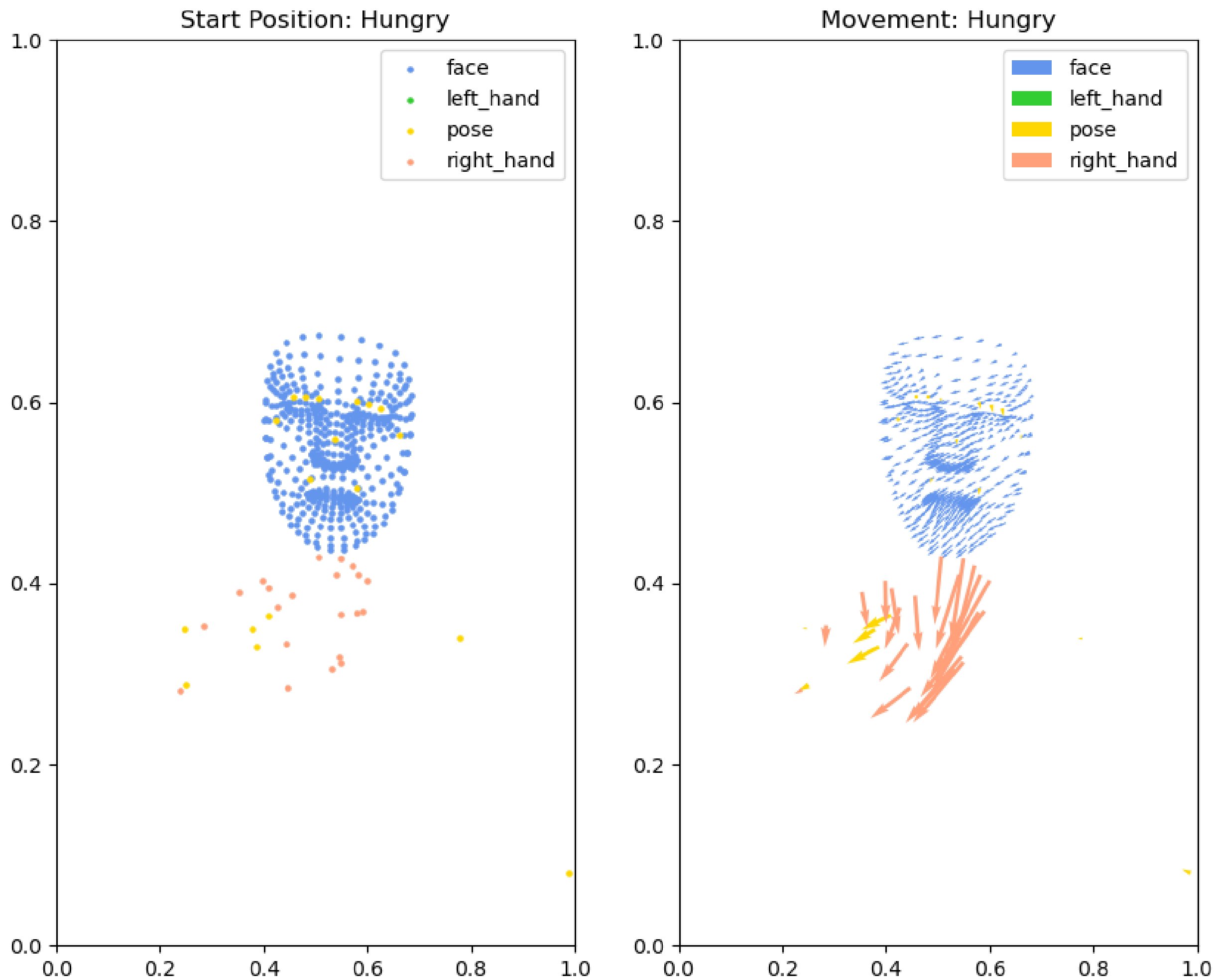
In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import json
import sklearn
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, log_loss, classification_report,
                             roc_auc_score, ConfusionMatrixDisplay,
                             confusion_matrix)
from imblearn.over_sampling import SMOTE

sklearn.set_config(display='diagram')
%matplotlib inline
```

Exploring one Sign example - Hungry

Lets take a look at what the landmark positions and change vectors look like for a single file

In [12]:

```
# load in parquet file
df = pd.read_parquet('data/1005995721.parquet')
# invert y column to vizualize upright
df['y'] = 1-df['y']

# set up axes and iterable titles and colors
fig, axes = plt.subplots(ncols=2,figsize=(10,8))
colors=['cornflowerblue','limegreen','gold','lightsalmon']
titles = ['Start Position: Hungry', 'Movement: Hungry']

# dataframes containing info from first and last frame of video
first_frame = df.loc[df.frame==df.frame.min()]
last_frame = df.loc[df.frame==df.frame.max()]

for i, type in enumerate(list(df.type.unique())):
    # select only landmarks of type == type
    # (from [face,right_hand,left_hand,pose])
    start = first_frame.loc[df.type == type]
    end = last_frame.loc[df.type == type]
    # Vector origin location
    X = start['x'].to_list()
    Y = start['y'].to_list()

    # Directional vectors
    U = np.array(end['x'].to_list()) - np.array(X)
    V = np.array(end['y'].to_list()) - np.array(Y)

    # Creating plot
    axes[0].scatter(X,Y, c=colors[i], label=type,s=5)
    axes[1].quiver(X, Y, U, V,
                   color=colors[i],
                   units='xy',
                   scale=1,
                   headwidth=2.5,
                   label=type)

for i, ax in enumerate(axes):
    # x-lim and y-lim
    ax.set_xlim(0, 1)
    ax.set_ylim(0, 1)

    ax.set_title(titles[i])
    ax.legend()
plt.show()
```



Load Data and Train-Test-Split

The Full dataset was loaded in with AquiringData.ipynb
Columns:

- sign : 87 unique signs
- *type* (face: 468* 4 columns, left_hand: 21* 4 columns, right_hand: 21* 4 columns, pose: 31*4 columns)
  - px_i_type : starting x position of the ith landmark, from landmarks in *type*
  - py_i_type : starting y position of the ith landmark, from landmarks in *type*
  - dx_i_type : total change in x position of the ith landmark, from landmarks in *type*
  - dy_i_type : total change in y position of the ith landmark, from landmarks in *type*

In [13]:
```python
# Load Meta Data
meta_data = pd.read_csv('data/train.csv')

# Load Data
signs = pd.read_csv('data/all_targets.csv',index_col=0)['0'].to_list()
signs_5 = ['hungry','stay','drink','dad','sad']
dataset_5_signs = pd.read_csv('data/dataset_hungry_stay_drink_dad_sad.csv',
                              index_col=0)
dataset = pd.concat((dataset_5_signs,
                     pd.read_csv('data/dataset_round2_155.csv',
                                 index_col=0)),
                    axis=0)
# Load sign name to int mapping
with open('data/sign_to_prediction_index_map.json') as f:
    sign_map = json.load(f)

# fix columns name ordering from data preprocessing
col_names_fixed = pd.read_csv('data/col_names_fixed.csv',
                              index_col=0)['0'].values
dataset_5_signs.rename(
    columns={old:new for old, new in zip(dataset_5_signs.columns,
                                         col_names_fixed)},
    inplace=True)
dataset.rename(
    columns={old:new for old, new in zip(dataset_5_signs.columns,
                                         col_names_fixed)},
    inplace=True)

# Train Test Split 5 signs
X = dataset_5_signs.drop(columns='sign')
y = dataset_5_signs['sign'].map({sign:i for i, sign in enumerate(signs_5)})
X_train_5_signs, X_test_5_signs, y_train_5_signs, y_test_5_signs = \
    train_test_split(X, y, test_size=.25, stratify=y, random_state=42)
print('Small Dataset (5 signs), train test shapes:')
print(X_train_5_signs.shape,
      X_test_5_signs.shape,
      y_train_5_signs.shape,
      y_test_5_signs.shape)

# Train Test Split 87 signs
X = dataset.drop(columns='sign')
y = dataset['sign'].map({sign:i for i, sign in enumerate(signs)})
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=.25,
                                                    stratify=y,
                                                    random_state=42)
print('Full Dataset (5 signs), train test shapes:')
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
Small Dataset (5 signs), train test shapes:
(1447, 2172) (483, 2172) (1447,) (483,)
Full Dataset (5 signs), train test shapes:
(45390, 2172) (15130, 2172) (45390,) (15130,)
```

```
In [10]: # show dataset format and shape
display(dataset.head())
dataset.shape
```

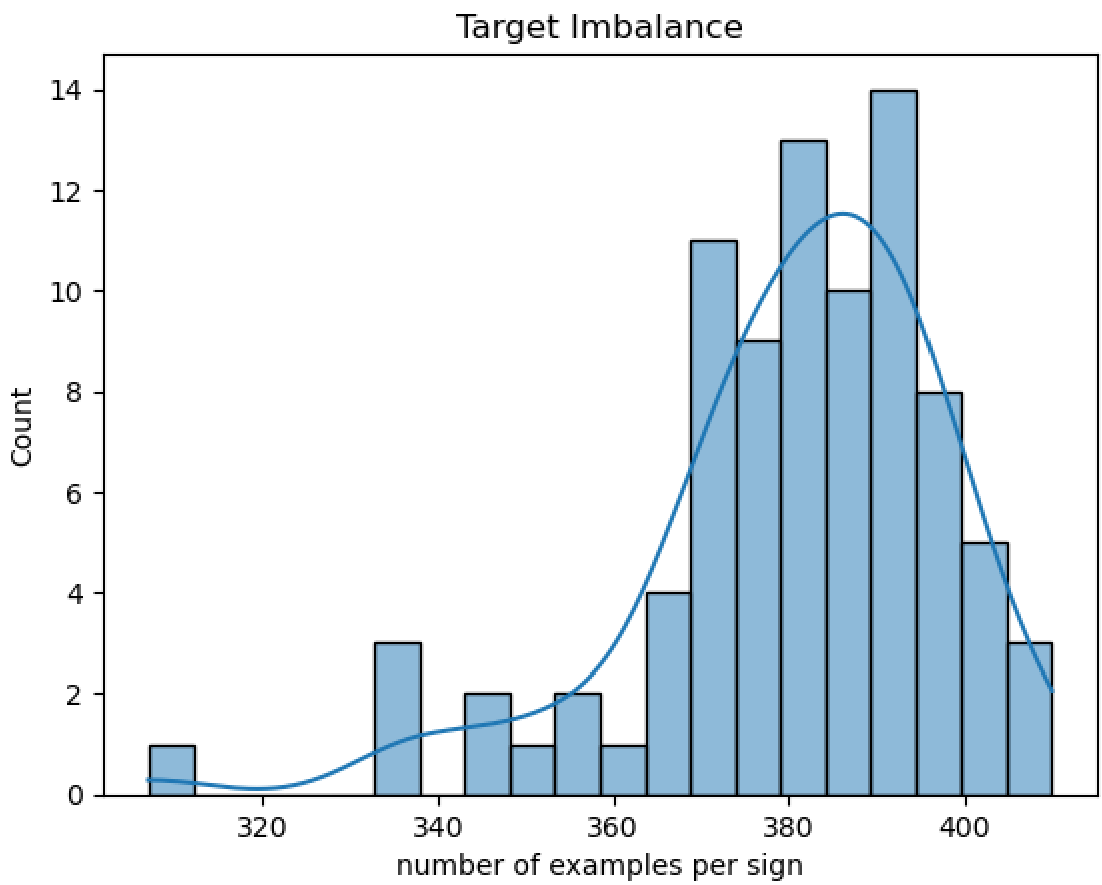
	px_0_face	py_0_face	dx_0_face	dy_0_face	px_1_face	py_1_face	dx_1_face	dy_1_face	px_2_fac
0	0.144412	0.770001	-0.036422	0.060955	0.220252	0.751034	-0.007117	0.059470	0.2948
1	0.228887	0.870846	0.149825	0.046881	0.217067	0.780410	0.173444	0.069344	0.2831
2	0.219266	0.694923	-0.047326	0.136267	0.246657	0.630376	-0.000493	0.144555	0.3156
3	0.265351	0.609593	-0.113243	0.169336	0.300004	0.556525	-0.051936	0.175018	0.3582
4	0.192178	0.910085	-0.109875	0.009503	0.231285	0.847868	-0.097434	0.014697	0.3053

5 rows × 2173 columns

```
Out[10]: (60520, 2173)
```

Vizualizing Target Imbalance

In [ ]:
```
# hisplot target column
sns.histplot(
    meta_data.loc[[sign in signs for sign in meta_data.sign]].sign.value_co
    kde=True,
    bins=20)
plt.xlabel('number of examples per sign')
plt.title('Target Imbalance')
plt.show()
```



Baseline model

Logistic Regression 5 signs

In [ ]:
```
# Set up pipeline
lr_small_model = Pipeline(steps=[('model',
                                  LogisticRegression(max_iter=1000))])
# fit with small dataset (5 total signs/targets)
lr_small_model.fit(X_train_5_signs, y_train_5_signs)
# show metrics
lr_small_pred = lr_small_model.predict(X_test_5_signs)
lr_small_report = classification_report(y_test_5_signs,
                                        lr_small_pred,
                                        target_names=signs_5,
                                        output_dict=True)
lr_small_metrics_df = pd.DataFrame(lr_small_report).transpose()
print('Mean Accuracy: ',lr_small_metrics_df['support']['accuracy'])
print('Mean Precision:',lr_small_metrics_df['precision']['macro avg'])
print('Mean Recall:   ',lr_small_metrics_df['recall']['macro avg'])
print('Mean f1-score: ',lr_small_metrics_df['f1-score']['macro avg'])
lr_small_metrics_df
```

```
Mean Accuracy:  0.8322981366459627
Mean Precision: 0.8341454272863569
Mean Recall:    0.8330015616548971
Mean f1-score:  0.8323935003390449
```

	precision	recall	f1-score	support
hungry	0.833333	0.833333	0.833333	96.000000
stay	0.788462	0.872340	0.828283	94.000000
drink	0.804348	0.740000	0.770833	100.000000
dad	0.908046	0.831579	0.868132	95.000000
sad	0.836538	0.887755	0.861386	98.000000
accuracy	0.832298	0.832298	0.832298	0.832298
macro avg	0.834145	0.833002	0.832394	483.000000
weighted avg	0.833945	0.832298	0.831947	483.000000

Model Iterations

Model Iteration 1 - Logistic Regression

Hyperparameter tuning with 87 signs

In [21]:

```
# set up pipeline
lr_pipe = Pipeline(steps=[('model', LogisticRegression())])

# parameters to gridsearch
param_grid = {'model__C':[1e-1,1],
              'model__max_iter':[500,1000],
              'model__class_weight':['balanced',None],
              'model__tol':[1e-4]}
# declare and run gridsearch
gs_lr_pipe = GridSearchCV(estimator=lr_pipe, param_grid=param_grid)
gs_lr_pipe.fit(X_train,y_train)
```

In [22]:
```
# save best linear regression model
lr_best_model = gs_lr_pipe.best_estimator_
display(lr_best_model)
# show metrics
lr_pred = lr_best_model.predict(X_test)
lr_report = classification_report(y_test,
                                  lr_pred,
                                  target_names=signs,
                                  output_dict=True)
lr_metrics_df = pd.DataFrame(lr_report).transpose()
print('Mean Accuracy: ',lr_metrics_df['support']['accuracy'])
print('Mean Precision:',lr_metrics_df['precision']['macro avg'])
print('Mean Recall:   ',lr_metrics_df['recall']['macro avg'])
print('Mean f1-score: ',lr_metrics_df['f1-score']['macro avg'])
lr_metrics_df
```

```
/Users/alexanderdaffara/opt/anaconda3/envs/tensorflow/lib/python3.10/site
-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfg
s failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://s
cikit-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression (https://scikit-learn.org/stable/modules/linear_model.html#logis
tic-regression)
  n_iter_i = _check_optimize_result(
```

```
Pipeline(steps=[('model', LogisticRegression(max_iter=1000))])
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
Mean Accuracy:  0.4922009253139458
Mean Precision: 0.5277185706225866
Mean Recall:    0.43162404117831177
Mean f1-score:  0.44718441676115345
```

Out[22]:

	precision	recall	f1-score	support
pig	0.600000	0.358696	0.448980	92.000000
elephant	0.311628	0.350785	0.330049	191.000000
mad	0.406780	0.408163	0.407470	294.000000
finger	0.409836	0.352113	0.378788	284.000000
green	0.475765	0.781971	0.591594	477.000000
...	...	...	...	...
dad	0.875000	0.819149	0.846154	94.000000
sad	0.868132	0.806122	0.835979	98.000000
accuracy	0.492201	0.492201	0.492201	0.492201
macro avg	0.527719	0.431624	0.447184	15130.000000
weighted avg	0.501030	0.492201	0.472397	15130.000000

90 rows × 4 columns

Model iteration 2 - Random Forest

Hyperparameter tuning with 87 signs

In [58]:

```
# set up pipeline
rf_pipe = Pipeline(steps=[('model',
                           RandomForestClassifier(random_state=42))])

# parameters to gridsearch
param_grid = {'model__max_depth':[2,3,4,10],
              'model__n_estimators':[500,1000],
              'model__class_weight':['balanced',
                                     'balanced_subsample',
                                      None],
              'model__tol':[1e-4]}
# declare and run gridsearch
gs_rf_pipe = GridSearchCV(estimator=rf_pipe, param_grid=param_grid)
gs_rf_pipe.fit(X_train,y_train)
```

In [60]:
```
# save best random forest model
rf_best_model = gs_rf_pipe.best_estimator_
display(rf_best_model)
# show metrics
rf_pred = rf_best_model.predict(X_test)
rf_report = classification_report(y_test,
                                  rf_pred,
                                  target_names=signs,
                                  output_dict=True)
rf_metrics_df = pd.DataFrame(rf_report).transpose()
print('Mean Accuracy: ',rf_metrics_df['support']['accuracy'])
print('Mean Precision:',rf_metrics_df['precision']['macro avg'])
print('Mean Recall:   ',rf_metrics_df['recall']['macro avg'])
print('Mean f1-score: ',rf_metrics_df['f1-score']['macro avg'])
rf_metrics_df
```

```
Pipeline(steps=[('model', RandomForestClassifier(random_state=42))])
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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```
Mean Accuracy:  0.7476536682088566
Mean Precision: 0.6909030004854534
Mean Recall:    0.5984600752722209
Mean f1-score:  0.5980725269969054
```

Out[60]:

	precision	recall	f1-score	support
pig	0.485714	0.369565	0.419753	92.000000
elephant	0.776744	0.874346	0.822660	191.000000
mad	0.801136	0.959184	0.873065	294.000000
finger	0.725594	0.968310	0.829563	284.000000
green	0.763200	1.000000	0.865699	477.000000
...	...	...	...	...
dad	0.903614	0.797872	0.847458	94.000000
sad	0.793814	0.785714	0.789744	98.000000
accuracy	0.747654	0.747654	0.747654	0.747654
macro avg	0.690903	0.598460	0.598073	15130.000000
weighted avg	0.726252	0.747654	0.707062	15130.000000

90 rows × 4 columns

Model Iteration 3 - Histogram XGBoost

Hyperparameter tuning with 87 signs

In [26]:

```
# set up pipeline
hxgb_pipe = Pipeline(steps = [('model',
                               XGBClassifier(subsample = 1,
                                             tree_method='gpu_hist',
                                             predictor='gpu_predictor',
                                             random_state=42) )])
# parameters to gridsearch
param_grid = {'model__max_depth':[2,3,4,10],
              'model__n_estimators':[100,300,500],
              'model__max_bin':[32,64],
              'model__colsample_bytree':[.8,.9,1]}
# declare and run gridsearch
gs_hxgb_pipe = GridSearchCV(estimator=hxgb_pipe, param_grid=param_grid)
gs_hxgb_pipe.fit(X_train,y_train)
```

In [25]:
```python
# save best histXGBoost model
hxgb_best_model = gs_hxgb_pipe.best_estimator_
display(hxgb_best_model)
# show metrics
hxgb_pred = hxgb_best_model.predict(X_test)
hxgb_report = classification_report(y_test,
                                     hxgb_pred,
                                     target_names=signs,
                                     output_dict=True)
hxgb_metrics_df = pd.DataFrame(hxgb_report).transpose()
print('Mean Accuracy: ',hxgb_metrics_df['support']['accuracy'])
print('Mean Precision:',hxgb_metrics_df['precision']['macro avg'])
print('Mean Recall:   ',hxgb_metrics_df['recall']['macro avg'])
print('Mean f1-score: ',hxgb_metrics_df['f1-score']['macro avg'])
hxgb_metrics_df
```

```
Pipeline(steps=[('model',
                 XGBClassifier(base_score=0.5, booster='gbtree', callback
s=None,
                               colsample_bylevel=1, colsample_bynode=1,
                               colsample_bytree=1, early_stopping_rounds=
None,
                               enable_categorical=False, eval_metric=Non
e,
                               feature_types=None, gamma=0, gpu_id=-1,
                               grow_policy='depthwise', importance_type=N
one,
                               interaction_constraints='',
                               learning_rate=0.300000012, max_bin=64,
                               max_cat_threshold=64, max_cat_to_onehot=4,
                               max_delta_step=0, max_depth=4, max_leaves=
0,
                               min_child_weight=1, missing=nan,
                               monotone_constraints='()', n_estimators=30
0,
                               n_jobs=0, num_parallel_tree=1,
                               objective='multi:softprob',
                               predictor='gpu_predictor', ...))])
```

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```
Mean Accuracy:  0.8015862524785194
Mean Precision: 0.7349734200627183
Mean Recall:    0.6845124696429522
Mean f1-score:  0.6952299364721685
```

Out[25]:

	precision	recall	f1-score	support
pig	0.632353	0.467391	0.537500	92.000000
elephant	0.799065	0.895288	0.844444	191.000000
mad	0.850746	0.969388	0.906200	294.000000
finger	0.774648	0.968310	0.860720	284.000000
green	0.889925	1.000000	0.941757	477.000000
...	...	...	...	...
dad	0.827957	0.819149	0.823529	94.000000
sad	0.806452	0.765306	0.785340	98.000000
accuracy	0.801586	0.801586	0.801586	0.801586
macro avg	0.734973	0.684512	0.695230	15130.000000
weighted avg	0.783247	0.801586	0.782894	15130.000000

90 rows × 4 columns

Final Model - Histogram XGBoost + SMOTE

In [27]:

```
X_train_smote, y_train_smote = \
    SMOTE(sampling_strategy='not majority').fit_resample(X_train,y_train)
X_train_smote.shape, y_train_smote.shape
```

Out[27]: ((152685, 2172), (152685,))

Hyperparameter tuning with 87 signs

In [30]:

```
# set up pipeline
hxgb_pipe = Pipeline(steps = [('model',
                               XGBClassifier(subsample = 1,
                                             tree_method='gpu_hist',
                                             predictor='gpu_predictor',
                                             random_state=42) )])
# parameters to gridsearch
param_grid = {'model__max_depth':[2,3,4,10],
              'model__n_estimators':[100,300,500],
              'model__max_bin':[32,64],
              'model__colsample_bytree':[.8,.9,1]}
# declare and run gridsearch
gs_hxgb_pipe = GridSearchCV(estimator=hxgb_pipe, param_grid=param_grid)
gs_hxgb_pipe.fit(X_train_smote,y_train_smote)
```

In [32]:
```python
# save best histXGBoost (+SMOTE) model
hxgb_best_model = gs_hxgb_pipe.best_estimator_
display(hxgb_best_model)
# show metrics
hxgb_pred = hxgb_best_model.predict(X_test)
hxgb_report = classification_report(y_test,
                                    hxgb_pred,
                                    target_names=signs,
                                    output_dict=True)
hxgb_metrics_df = pd.DataFrame(hxgb_report).transpose()
print('Mean Accuracy: ',hxgb_metrics_df['support']['accuracy'])
print('Mean Precision:',hxgb_metrics_df['precision']['macro avg'])
print('Mean Recall:   ',hxgb_metrics_df['recall']['macro avg'])
print('Mean f1-score: ',hxgb_metrics_df['f1-score']['macro avg'])
hxgb_metrics_df
```

```
Pipeline(steps=[('model',
                 XGBClassifier(base_score=0.5, booster='gbtree', callback
s=None,
                               colsample_bylevel=1, colsample_bynode=1,
                               colsample_bytree=1, early_stopping_rounds=
None,
                               enable_categorical=False, eval_metric=Non
e,
                               feature_types=None, gamma=0, gpu_id=-1,
                               grow_policy='depthwise', importance_type=N
one,
                               interaction_constraints='',
                               learning_rate=0.300000012, max_bin=64,
                               max_cat_threshold=64, max_cat_to_onehot=4,
                               max_delta_step=0, max_depth=4, max_leaves=
0,
                               min_child_weight=1, missing=nan,
                               monotone_constraints='()', n_estimators=30
0,
                               n_jobs=0, num_parallel_tree=1,
                               objective='multi:softprob',
                               predictor='gpu_predictor', ...))])
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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```
Mean Accuracy:  0.8606080634500991
Mean Precision: 0.8385839842573934
Mean Recall:    0.8616946671629468
Mean f1-score:  0.8480013603800165
```

Out[32]:

	precision	recall	f1-score	support
pig	0.626506	0.565217	0.594286	92.000000
elephant	0.872727	0.753927	0.808989	191.000000
mad	0.885714	0.843537	0.864111	294.000000
finger	0.905138	0.806338	0.852886	284.000000
green	0.944690	0.895178	0.919268	477.000000
...	...	...	...	...
dad	0.978261	0.957447	0.967742	94.000000
sad	0.989130	0.928571	0.957895	98.000000
accuracy	0.860608	0.860608	0.860608	0.860608
macro avg	0.838584	0.861695	0.848001	15130.000000
weighted avg	0.866093	0.860608	0.861725	15130.000000

90 rows × 4 columns

Feature Importance

Although not always significant, I'll save the features that led to the most information gain during training of XGBoost

In [42]:
```
# get feature importances from model, save to hxgb_feat_imp dataframe
hxgb_feat_imp = pd.DataFrame(hxgb_best_model['model'].feature_importances_,
                             index=col_names_fixed[:-1],
                             columns=['importance']).reset_index()
# include info columns
hxgb_feat_imp['type'] = \
    hxgb_feat_imp['index'].map(lambda x: x.split('_')[-1])
hxgb_feat_imp['kinematic'] = \
    hxgb_feat_imp['index'].map(lambda x: x.split('_')[0][0])
hxgb_feat_imp['landmark'] = \
    hxgb_feat_imp['index'].map(lambda x: int(x.split('_')[1]))
# rename feature name column to id
hxgb_feat_imp.rename(columns={'index':'id'}, inplace=True)
# sort by highest importance
top_imp = hxgb_feat_imp.sort_values(by='importance',
                                    ascending=False).head(50)
top_imp.head()
```

Out[42]:

	id	importance	type	kinematic	landmark
8	px_2_left_hand	0.006024	hand	p	2
1201	py_246_face	0.005638	face	p	246
560	px_86_face	0.005052	face	p	86
2133	py_11_right_hand	0.004949	hand	p	11
1512	px_324_face	0.004600	face	p	324

Landmark analysis

"Dad" and "Airplane" have very similar signs, although the model scored exceptionally well with those targets. This if useful for PopSign! to show the user the difference between the two signs.

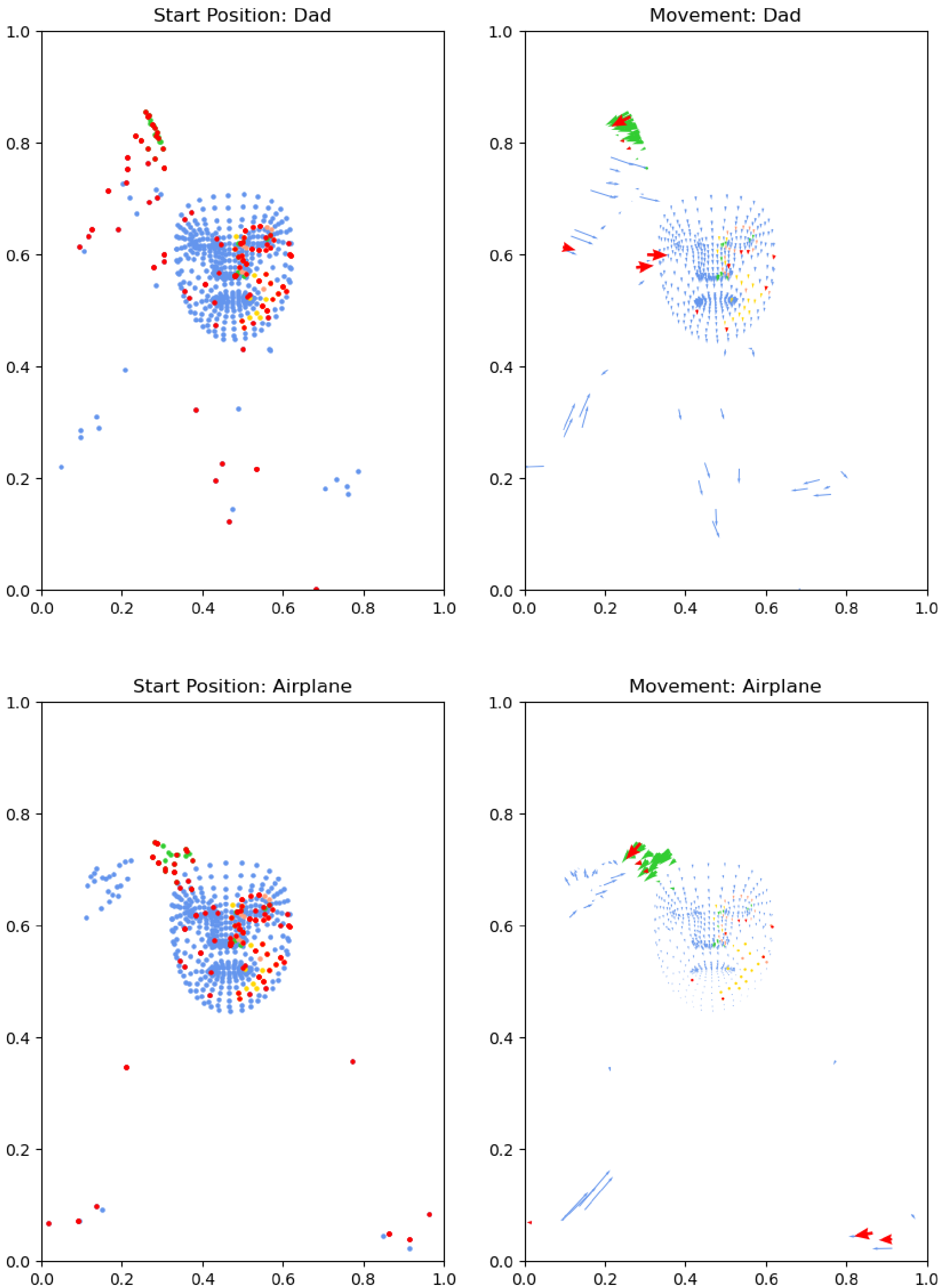
Lets look now at a visualization that averages all the test results that were predicted as "Dad" and "Airplane", and highlight the points and vectors that were most important to our model.

In [ ]:
```
# show final model metrics for dad and airplane
hxgb_metrics_df.loc[['dad','airplane']]
```

	precision	recall	f1-score	support
dad	0.978261	0.957447	0.967742	94.0
airplane	0.931655	0.877966	0.904014	295.0

```
In [54]: # query list for signs to vizualize
sign_queries = ['dad','airplane']
# convert to integer ids used by model for the targets
sign_query_ids = \
    [signs.index(sign_query) for sign_query in sign_queries]
# make a dataframe from y_test set,
# we will subset it with our sign_queries
yt_df = pd.DataFrame(y_test)

# set up axes, colors and titles
fig, axes = plt.subplots(ncols=2,
                         nrows=len(sign_queries),
                         figsize=(10,14))
colors=['cornflowerblue','gold','limegreen','lightsalmon']
titles = [['Start Position: Dad', 'Movement: Dad'],
          ['Start Position: Airplane', 'Movement: Airplane']]

# iterate through sign_queries
for sign_query_iter, sign_query_id in enumerate(sign_query_ids):
    # subset of test set labelled dad and airplane
    sign_query_res = \
        X_test.loc[yt_df.loc[yt_df.sign==sign_query_id].index]

    ax_id = {'p':0,'d':1}

    cols = list(sign_query_res.columns)
    # boolean lists to select columns by their attributes from sign_query_r
    px_keep = [col.split('_')[0] != 'px' for col in cols]
    dx_keep = [col.split('_')[0] != 'dx' for col in cols]
    py_keep = [col.split('_')[0] != 'py' for col in cols]
    dy_keep = [col.split('_')[0] != 'dy' for col in cols]
    face_keep = [col.split('_')[-1] != 'face' for col in cols]
    pose_keep = [col.split('_')[-1] != 'pose' for col in cols]
    rh_keep = [col.split('_')[-2] != 'right' for col in cols]
    lh_keep = [col.split('_')[-2] != 'left' for col in cols]

    types = [face_keep,lh_keep,pose_keep,rh_keep]
    type_name = ['face','left_hand','pose','right_hand']

    # iterate through types
    for type_i, type_keep in enumerate(types):
        # Vector origin location
        X = sign_query_res.drop(
            columns=[cols[i] for i in range(len(cols)) \
                     if px_keep[i] or type_keep[i]]).mean().values
        Y = 1-sign_query_res.drop(
            columns=[cols[i] for i in range(len(cols)) \
                     if py_keep[i] or type_keep[i]]).mean().values

        # Directional vectors
        U = sign_query_res.drop(
            columns=[cols[i] for i in range(len(cols)) \
                     if dx_keep[i] or type_keep[i]]).mean().values
        V = -sign_query_res.drop(
            columns=[cols[i] for i in range(len(cols)) \
                     if dy_keep[i] or type_keep[i]]).mean().values
        # Creating plot
```

```
        axes[sign_query_iter][0].scatter(
            X,Y, c=colors[type_i], label=type_name[type_i],s=5)
        axes[sign_query_iter][1].quiver(
            X, Y, U, V, color=colors[type_i], units='xy', scale=.5,
            headwidth=2.5, label=type_name[type_i])

    # iterate through sorted list of important features
    for idx in top_imp.index:
        feat = top_imp.loc[idx]
        lm_keep = [col.split('_')[1] != str(feat['landmark']) for col in co
        X = sign_query_res.drop(
            columns=[cols[i] for i in range(len(cols)) \
                     if px_keep[i] or lm_keep[i]]).mean().values
        Y = 1-sign_query_res.drop(
            columns=[cols[i] for i in range(len(cols)) \
                     if py_keep[i] or lm_keep[i]]).mean().values
        U = sign_query_res.drop(
            columns=[cols[i] for i in range(len(cols)) \
                     if dx_keep[i] or lm_keep[i]]).mean().values
        V = -sign_query_res.drop(
            columns=[cols[i] for i in range(len(cols)) \
                     if dy_keep[i] or lm_keep[i]]).mean().values
        if feat['kinematic'] == 'p':
            axes[sign_query_iter][ax_id[feat['kinematic']]].scatter(
                X,Y,c='red', s=5)
        else:
            axes[sign_query_iter][ax_id[feat['kinematic']]].quiver(
                X, Y, U, V, color='red', units='xy', scale=.5, headwidth=4)

    # limit axes to only show range[0,1] (frame size)
    for i, ax in enumerate(axes[sign_query_iter]):
        # x-lim and y-lim
        ax.set_xlim(0, 1)
        ax.set_ylim(0, 1)

        ax.set_title(titles[sign_query_iter][i])
plt.show()
```



Conclusions and Future Improvements

- Scalable: Our final model maintains performance as we increase number of signs to predict.

- Lightweight: Model is intrinsically faster to train and predict compared to other sophisticated models.
- Optimized for common words.

As I continue work on this project I would like to explore extracting more information from each video file, and in the case of deployment for production, it would be good to add more signers and ensure the model adapts to new environments the signers find themselves in.

Learn More about MediaPipe's solutions: https://google.github.io/mediapipe/solutions/holistic.html (https://google.github.io/mediapipe/solutions/holistic.html)

Kaggle Competition Link: https://www.kaggle.com/competitions/asl-signs/overview (https://www.kaggle.com/competitions/asl-signs/overview)