Supplementary Material (C) - Code for Steps 2 through 4: Compiling Step 2 results and running Steps 3 and 4

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Abstract

Code accompanying the paper: "Soundscape descriptors in eighteen languages: translation and validation through listening experiments

1. Step 2: SEM Fit Score

```python
# Import the required packages
import pandas as pd
import seaborn as sns
from pathlib import Path
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit
import numpy as np
from datetime import datetime
import circumplex
import json
from scipy.spatial import procrustes
from tensorly.metrics.factors import congruence_coefficient

today = datetime.today().strftime("%Y-%m-%d")
```

```python
# Define the scales and angles to be used
scales = ["PAQ1", "PAQ2", "PAQ3", "PAQ4", "PAQ5", "PAQ6", "PAQ7", "PAQ8"]
eq_angles = [0, 45, 90, 135, 180, 225, 270, 315]

# Define the data and output folders
data_folder = Path("../data/")
output_folder = Path(f"../outputs/{today}")

# Load data
satp = pd.read_excel(data_folder / "SATP Dataset v1.4.xlsx")
```

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```python
# Load the results from the latest SEM analysis
sem_res = pd.read_csv(output_folder / "sem-fit-ipsatized.csv")
sem_res.drop("Unnamed: 0", axis=1, inplace=True)

# In some cases, the SEM flips the angles
# (i.e. vibrant is at 315 degrees instead of 45).
# This function checks for this and corrects it,
# to ensure all the scales are in the correct order,
# but without changing the relationship between the angles,
# as identified by the SEM.)

# First, get the angles from the SEM results
ang_df = sem_res[sem_res["Model Type"] == "Equal comm."][["Language"] + scales]
ang_df.set_index("Language", inplace=True)


def check_inverse_angles(language_angles):
    """Check if the angles are inverse"""
    if (
        language_angles[1] > language_angles[2]
        or language_angles[2] > language_angles[3]
    ):
        return True
    else:
        return False


# Then, check if the angles are inverse, and if so, correct them
for lang in ang_df.index:
    if check_inverse_angles(ang_df.loc[lang].values):
        ang_df.loc[lang][1:] = 360 - ang_df.loc[lang][1:]

ang_dict = ang_df.T.to_dict(orient="list")
ang_dict
```

```
{'eng': [0.0, 46.0, 94.0, 138.0, 177.0, 231.0, 275.0, 340.0],
 'arb': [0.0, 36.0, 45.0, 135.0, 167.0, 201.0, 242.0, 308.0],
 'cmn': [0.0, 18.0, 38.0, 154.0, 171.0, 196.0, 217.0, 318.0],
 'deu': [0.0, 64.0, 97.0, 132.0, 182.0, 254.0, 282.0, 336.0],
 'ell': [0.0, 72.0, 86.0, 133.0, 161.0, 233.0, 267.0, 328.0],
 'fra': [0.0, 69.0, 102.0, 129.0, 173.0, 246.0, 275.0, 325.0],
 'hrv': [0.0, 84.0, 93.0, 160.0, 173.0, 243.0, 273.0, 354.0],
 'ind': [0.0, 53.0, 104.0, 123.0, 139.0, 202.0, 284.0, 308.0],
 'ita': [0.0, 57.0, 104.0, 142.0, 170.0, 274.0, 285.0, 336.0],
 'jpn': [0.0, 46.0, 101.0, 138.0, 159.0, 271.0, 288.0, 339.0],
 'kor': [0.0, 56.0, 90.0, 124.0, 151.0, 251.0, 275.0, 288.0],
 'nld': [0.0, 43.0, 111.0, 125.0, 174.0, 257.0, 307.0, 341.0],
 'por': [0.0, 81.0, 121.0, 140.0, 171.0, 252.0, 275.0, 334.0],
 'spa': [0.0, 41.0, 103.0, 147.0, 174.0, 238.0, 279.0, 332.0],
 'swe': [0.0, 66.0, 87.0, 146.0, 175.0, 249.0, 275.0, 335.0],
 'tur': [0.0, 55.0, 97.0, 106.0, 157.0, 254.0, 289.0, 313.0]}
```

```
ang_dict["eng"]
```

```
[0.0, 46.0, 94.0, 138.0, 177.0, 231.0, 275.0, 340.0]
```

1.0.1. Calculate the SEM fit score

The SEM fit score is calculated by counting the number of fit indices that pass the pre-defined threshold. The thresholds are defined in the first part of the code. The thresholds are based on the thresholds used by Rogoza et al. (2021).

The first part of the code defines a dictionary named `thresholds` which contains the thresholds for different fit criteria used in SEM. These criteria include p-value (p), Comparative Fit Index (CFI), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Standardized Root Mean Square Residual (SRMR), and others.

The `incl_in_score` list is used to select which criteria will be included in the final score calculation. The `pass_thresh` and `tent_thresh` variables define the thresholds for passing and tentative passing scores, respectively.

The next part of the code calculates whether each SEM result passes the defined thresholds for each criterion. This is done by comparing the SEM result for each criterion to its respective threshold. The results of these comparisons are stored as boolean values in new columns in the `sem_res` DataFrame.

The final score for each SEM result is then calculated by summing the number of criteria each result passes. This score is stored as an integer in a new column in the `sem_res` DataFrame. The passing column categorizes each SEM result as 'Fail', 'Tentative', or 'Pass' based on its final score.

Finally, the results are saved to an Excel file and a subset of the results is displayed. The subset includes only the results for the "Equal comm." model type and is sorted by score in descending order.

```
# Define the thresholds for the SEM fit criteria
thresholds = {
    "CFI": 0.92,  #  Moshona et al 2023, Hu & Bentler 1999
    # "CFI": 0.9, # Rogoza 2021
    # "CFI": 0.95, # Good fit from Tarlao et al 2021
    "GFI": 0.90,  # Rogoza 2021
    # "AGFI": 0.85, # Rogoza 2021
    "SRMR": 0.08,  # Moshona et al 2023, Tarlao et al 2021, West (2023), Hu & Bentler (1999)
    # "MCSC": -0.7,
    # Removed RMSEA at the suggestion of
    # West, S.G., Wu, W., McNeish, D., & Savord, A. (2023).
    # Model Fit in Structural Equation Modeling.
    # In R.H. Hoyle, Handbook of structural equation modeling.
}

# Choose which criteria to include in the final score
# incl_in_score = ['CFI', 'GFI', 'AGFI', 'RMSEA'] # Rogoza
incl_in_score = ["CFI", "GFI", "SRMR"]

# Define the thresholds for the final score
pass_thresh = 3

# Calculate the final score
# CircE provides at most 3 digits after the decimal point,
# in some cases this is not enough to distinguish between
```

```python
#
sem_res["CFI_pass"] = sem_res["CFI"] >= thresholds["CFI"]
sem_res["GFI_pass"] = sem_res["GFI"] >= thresholds["GFI"]
sem_res["SRMR_pass"] = sem_res["SRMR"] < thresholds["SRMR"]

sem_res["Score"] = sem_res[[x + "_pass" for x in incl_in_score]].sum(axis=1)
sem_res["Score"] = sem_res["Score"].astype(int)
sem_res["passing"] = pd.cut(
    sem_res["Score"], bins=[0, pass_thresh, 7], labels=["Fail", "Pass"], right=False
)
# Save the results
sem_res.to_excel(output_folder / f"sem-fit-results.xlsx", index=False)
```

```python
sem_scores = sem_res[
    ["Language", "Model Type", "n", "m", "CFI", "GFI", "SRMR", "Score", "passing"]
].loc[sem_res["Model Type"] == "Equal comm."].sort_values("Language", ascending=True)
sem_scores.to_csv(output_folder / f"sem-scores.csv", index=False)
sem_scores
```

Table 1: SEM fit results

	Language	Model Type	n	m	CFI	GFI	SRMR	Score	passing
5	arb	Equal comm.	809	3	0.97	0.97	0.04	3	Pass
9	cmn	Equal comm.	1832	3	0.96	0.95	0.04	3	Pass
13	deu	Equal comm.	810	3	0.94	0.92	0.06	3	Pass
17	ell	Equal comm.	810	3	0.93	0.93	0.08	2	Fail
1	eng	Equal comm.	864	3	0.93	0.91	0.05	3	Pass
21	fra	Equal comm.	891	3	0.92	0.91	0.10	2	Fail
25	hrv	Equal comm.	864	3	0.95	0.93	0.06	3	Pass
29	ind	Equal comm.	891	3	0.93	0.92	0.08	2	Fail
33	ita	Equal comm.	810	3	0.94	0.93	0.07	3	Pass
37	jpn	Equal comm.	917	3	0.89	0.90	0.09	1	Fail
41	kor	Equal comm.	810	3	0.95	0.94	0.08	2	Fail
45	nld	Equal comm.	864	3	0.97	0.94	0.06	3	Pass
49	por	Equal comm.	1890	3	0.92	0.92	0.09	2	Fail
53	spa	Equal comm.	1647	3	0.92	0.91	0.06	3	Pass
57	swe	Equal comm.	945	3	0.94	0.92	0.05	3	Pass
61	tur	Equal comm.	918	3	0.93	0.92	0.08	2	Fail

```python
passing = (
    sem_res.loc[sem_res["Model Type"] == "Equal comm."]
    .query("passing != 'Fail'")["Language"]
    .values
)

satp = satp.query("Language in @passing")
```

1.0.2. Steps 3 and 4: Accurately locating circumplex items within each language

For this analysis, we use a custom Python package developed for this paper, called `circumplex` which can be installed from PyPI.

The process to do this is as follows:

1. For both the reference and test circumplex, calculate the mean value of each scale for each recording.
2. Calculate the SSM correlation between each scale of the reference circumplex and the test circumplex, in our case using the corrected angles.
3. Test the congruence betwen the empirical locations and theoretical expectations using the Procrustes congruence test (Rogoza et al., 2021).

We will be using the full dataset as the reference set and the data from each translation as the test set. This effectively means that we are testing whether each translation is able to locate the circumplex structure of the soundscape survey, consistently across all languages.

1.0.2.1. Congruence.

What Rogoza et al. (2021) (and Orthosim) refer to as Tucker's Congruence Coefficient is also commonly referred to as the cosine similarity (see the Tensorly documentation). We therefore use the sklearn implementation of cosine similarity to calculate the congruence between the empirical locations and theoretical expectations. This produces a matrix of cosine similarity values, which we then use to calculate the mean congruence, to match the model congruence from Rogoza et al. (2021).

We can confirm the equivalence of this method by comparing with the results from Rogoza et al. (2021) 's Orthosim analysis:

```python
def congruence(data1, data2, metric: ["cosine", "euclidean"] = "cosine"):
    from sklearn.metrics.pairwise import cosine_similarity
    from scipy.spatial.distance import cdist

    if metric == "cosine":
        sim = cosine_similarity(data1, data2)
    elif metric == "euclidean":
        sim = 1 - cdist(data1, data2, metric=metric)
    else:
        raise ValueError("metric must be 'cosine' or 'euclidean'")
    # Get the diagonal values which compare against the appropriate angles
    cong_vals = np.diag(sim)
    return np.mean(cong_vals), cong_vals


# Data from Rogoza
data2 = np.array([[-0.59, -0.8], [-1, -0.05], [-0.5, 0.87]])
data1 = np.array([[-0.71, -0.71], [-1, 0], [-0.71, 0.71]])

model_congruence, scale_congruence = congruence(data1, data2)

print("Model Congruence == 0.984: ", np.round(model_congruence, 3) == 0.984)
print("Vulnerability Congruence == 0.99: ", np.round(scale_congruence[0], 2) == 0.99)
print("Antagonism Congruence == 1.0: ", np.round(scale_congruence[1], 2) == 1.0)
print("Grandiosity Congruence == 0.97: ", np.round(scale_congruence[2], 2) == 0.97)
```

```
Model Congruence == 0.984:  True
Vulnerability Congruence == 0.99:  True
Antagonism Congruence == 1.0:  True
Grandiosity Congruence == 0.97:  True
```

1.0.2.2. Procrustes.

However, it appears that, despite Rogoza et al. (2021) 's description, this method is not actually based on a Procrustes analysis. The equivalent distance metric from a Procrustes method would be the rotational-based Procrustes distance, i.e. the squared Froebenius norm of the difference between the two orthogonal matrices. See Andreella et al. (2023):

> Instead, the second distance exploits the orthogonal matrix parameters solution of the Procrustes problem. The rotational-based distance computes the squared Frobenius distance between these estimated orthogonal matrices. As we will see, this metric measures the level of dissimilarity/similarity in orientation between matrices/subjects before functional alignment.

As such, we can also calculate this distance using the `procrustes` package:

```python
def procrustes_distance(
    data1, data2, procrustes_type="orthogonal", translate=True, scale=True
):
    if procrustes_type == "orthogonal":
        from procrustes import orthogonal

        pro_res = orthogonal(data1, data2, translate=translate, scale=scale)
    elif procrustes_type == "rotational":
        from procrustes import rotational

        pro_res = rotational(data1, data2, translate=translate, scale=scale)
    elif procrustes_type == "generic":
        from procrustes import generic

        pro_res = generic(data1, data2, translate=translate, scale=scale)
    return pro_res.error
```

```python
def prepare_congruence_matrices(ssm_table, target_angles=eq_angles):
    """Prepare the congruence matrices for the SSM results"""
    # Get the data from the SSM table
    # data2 = np.array((np.cos(np.deg2rad(ssm_table['displacement'])), np.sin(np.deg2rad(ssm_table['di
    data2 = ssm_table[["xval", "yval"]].values
    # Get the data from the target angles
    data1 = np.ones_like(data2)
    data1[:, 0] = np.cos(np.deg2rad(target_angles))
    data1[:, 1] = np.sin(np.deg2rad(target_angles))

    return data1, data2
```

Based on the proof given in **?**, given that the input matrices are scaled (i.e. `rotational(scale=True)`), then the Procrustes distance is a true distance measure which obeys $0 < p(X, Y) < 1$ (Bakhtiar and Siswadi, 2015, 322). Therefore we can convert the Procrustes distance to a similarity measure by subtracting it from 1.

```python
overall_means = satp.groupby(["Recording"])[scales].mean().reset_index(drop=True)

lang_rec_means = satp.groupby(["Language", "Recording"])[scales].mean()
lang_rec_means.reset_index(inplace=True)
```

```python
def test_language_locations(
    test_lang_means,
    test_lang,
    test_angles,
    target_angles=eq_angles,
    scales=("PAQ1", "PAQ2", "PAQ3", "PAQ4", "PAQ5", "PAQ6", "PAQ7", "PAQ8"),
):
    """Test the congruence of the language locations with the target angles"""
    test_res = []
    for scale in scales:
        corrs = test_lang_means.corrwith(overall_means[scale])
        ssm_res = circumplex.SSMParams(
            corrs,
            scales,
            test_angles,
            scale,
        )
        test_res.append(ssm_res)

    test_ssm = circumplex.SSMResults(test_res)

    data1, data2 = prepare_congruence_matrices(
        test_ssm.table, target_angles=target_angles
    )
    test_model_congruence, test_scale_congruences = congruence(
        data1, data2, metric="cosine"
    )
    pro_sim = 1 - procrustes_distance(data1, data2, procrustes_type="rotational")
    return test_ssm, test_model_congruence, test_scale_congruences, pro_sim


locating_corr_angles = {}
locating_eq_angles = {}
for test_lang in lang_rec_means.Language.unique():
    test_lang_means = lang_rec_means.query("Language == @test_lang")[
        scales
    ].reset_index(drop=True)

    locating_eq_angles[test_lang] = test_language_locations(
        test_lang_means, test_lang, test_angles=eq_angles, target_angles=eq_angles
    )
    locating_corr_angles[test_lang] = test_language_locations(
        test_lang_means,
        test_lang,
        test_angles=ang_dict[test_lang],
        target_angles=eq_angles,
    )
```

1.0.3. Step 3 Results

```
fit_results = pd.DataFrame.from_dict(
    {key: locating_corr_angles[key][0].table.r2 for key in locating_corr_angles.keys()}
).T
fit_results.round(3)
```

Table 2: Fit results for locating the general circumplex within each language

	PAQ1	PAQ2	PAQ3	PAQ4	PAQ5	PAQ6	PAQ7	PAQ8
arb	0.998	1.000	0.996	0.995	0.998	0.999	0.997	0.995
cmn	0.995	0.997	0.993	0.994	0.999	0.999	0.994	0.993
deu	0.979	0.999	0.999	0.998	0.998	0.998	0.999	0.998
eng	0.997	0.998	0.999	0.996	0.997	0.999	0.999	0.994
hrv	0.997	0.998	0.995	0.995	0.997	0.997	0.996	0.991
ita	0.914	0.995	0.998	0.985	0.980	0.989	0.997	0.977
nld	0.996	0.998	0.998	0.998	0.998	0.996	0.999	0.998
spa	0.998	0.996	0.998	0.998	0.998	0.996	0.998	0.999
swe	0.996	0.998	0.997	0.997	0.996	0.997	0.997	0.996

1.0.4. Step 4 Results

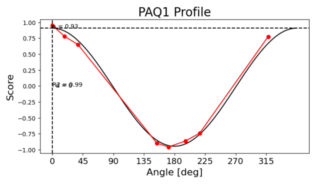
```
congruence_df = pd.DataFrame(
    {
        "Language": list(locating_eq_angles.keys()),
        "Eq Ang Model": [x[1] for x in locating_eq_angles.values()],
        "Corr Ang Model": [x[1] for x in locating_corr_angles.values()],
        "Eq Ang Procrustes": [x[3] for x in locating_eq_angles.values()],
        "Corr Ang Procrustes": [x[3] for x in locating_corr_angles.values()],
    }
)
congruence_df.round(3)
```

Table 3: Correspondence between the general circumplex and the language-specific circumplex

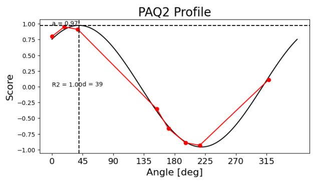
	Language	Eq Ang Model	Corr Ang Model	Eq Ang Procrustes	Corr Ang Procrustes
0	arb	0.982	0.927	0.969	0.984
1	cmn	0.922	0.987	0.855	0.984
2	deu	0.991	0.970	0.981	0.978
3	eng	0.992	0.985	0.985	0.986
4	hrv	0.987	0.979	0.983	0.984
5	ita	0.991	0.960	0.981	0.971
6	nld	0.983	0.982	0.952	0.981
7	spa	0.989	0.989	0.974	0.983
8	swe	0.990	0.983	0.979	0.981

1.0.5. Profile Plots

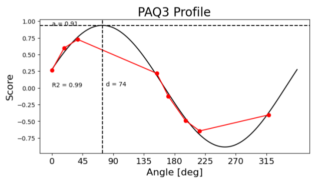
```
for res in locating_corr_angles["cmn"][0].results:
    res.profile_plot()
    plt.show()
```



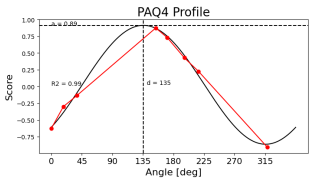
(a) PAQ1



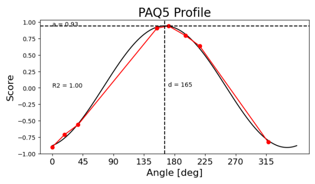
(b) PAQ2



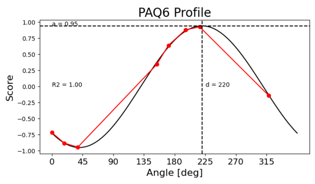
(c) PAQ3



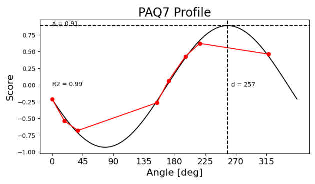
(d) PAQ4



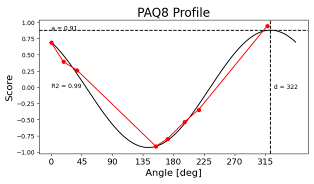
(e) PAQ5



(f) PAQ6



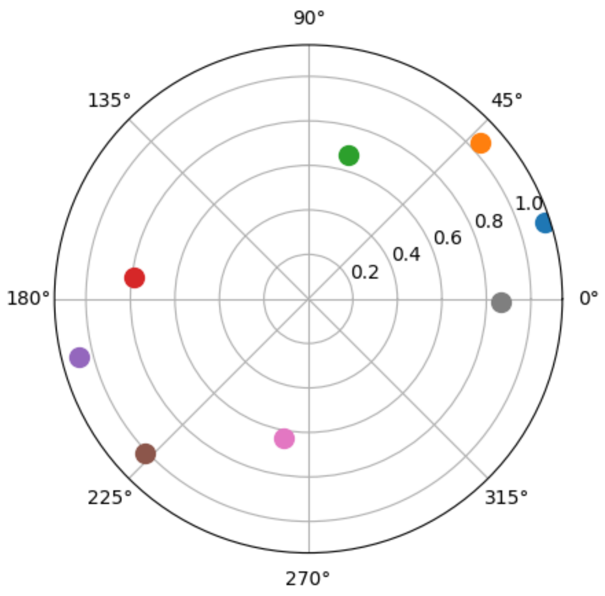
(g) PAQ7



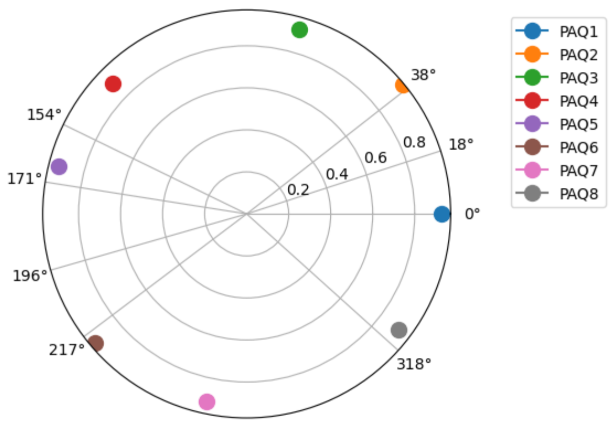
(h) PAQ8

Figure 1: Profile plots for the Mandarin (cmn) translation

```python
from matplotlib import colormaps

fig, ax = plt.subplots(subplot_kw=dict(projection="polar"))
colors = colormaps.get_cmap("tab10").colors
colors = iter(colors)
for res in locating_eq_angles["cmn"][0].results:
    ax.plot(
        np.deg2rad(res.displacement),
        res.amplitude,
        color=next(colors),
        marker="o",
        markersize=10,
        label=res.label,
    )

# locating_eq_angles['cmn'][0].plot(legend=False)
plt.show()
# locating_corr_angles['cmn'][0].plot()

fig, ax = plt.subplots(subplot_kw=dict(projection="polar"))
colors = colormaps.get_cmap("tab10").colors
colors = iter(colors)
for res in locating_corr_angles["cmn"][0].results:
    ax.plot(
        np.deg2rad(res.displacement),
        res.amplitude,
        color=next(colors),
        marker="o",
        markersize=10,
        label=res.label,
    )
ax.set_thetagrids(locating_corr_angles["cmn"][0].results[0].angles)
ax.legend(loc="upper right", bbox_to_anchor=(1.4, 1.0))
plt.show()
```



(a) Equal angles



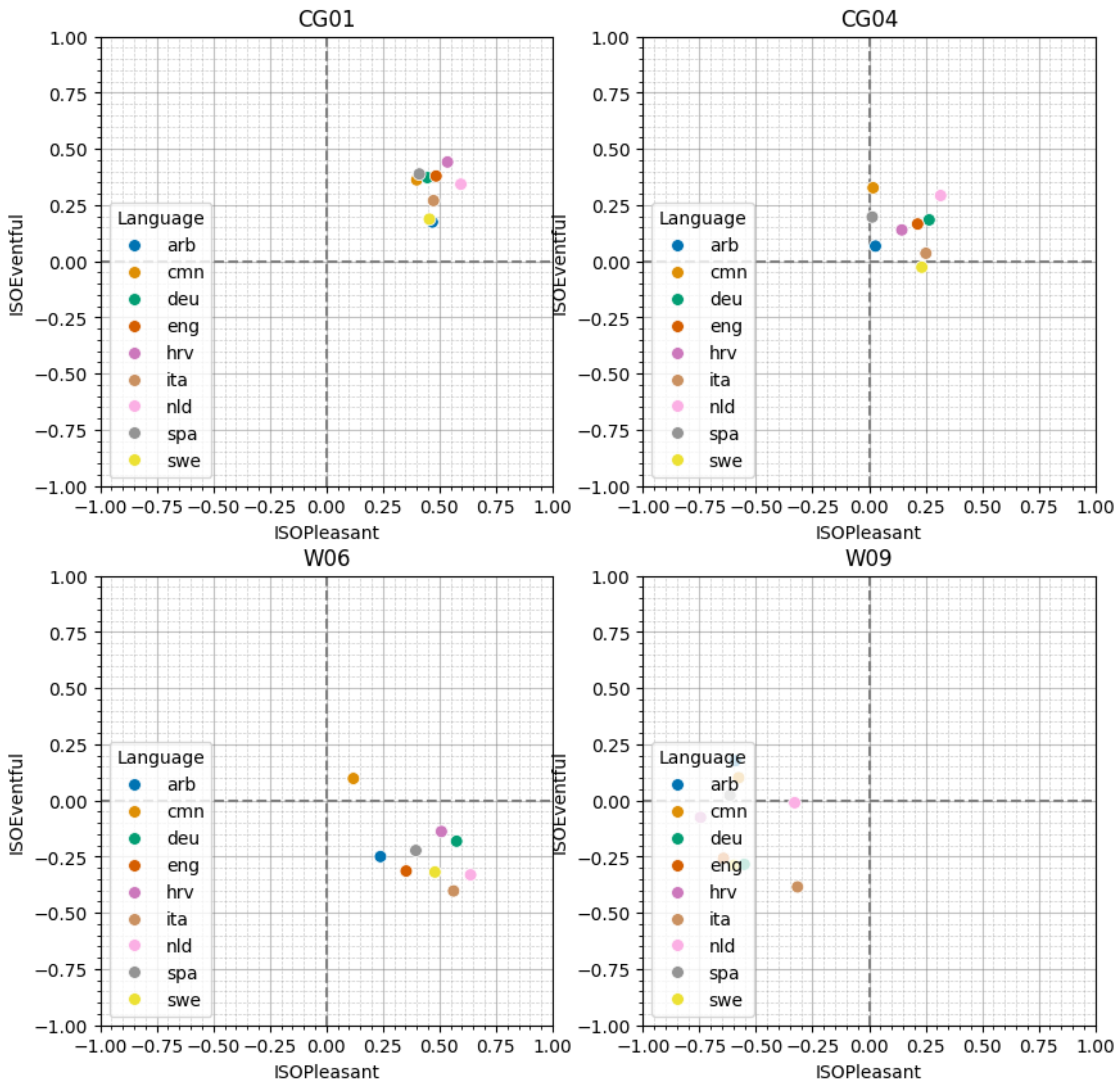
(b) Corrected angles

Figure 2: Locating the language-specific circumplex for Mandarin, using equal angles and corrected angles

1.1. Using the corrected angles for ISO 12913-3 and Mitchell et al. (2022) style analysis

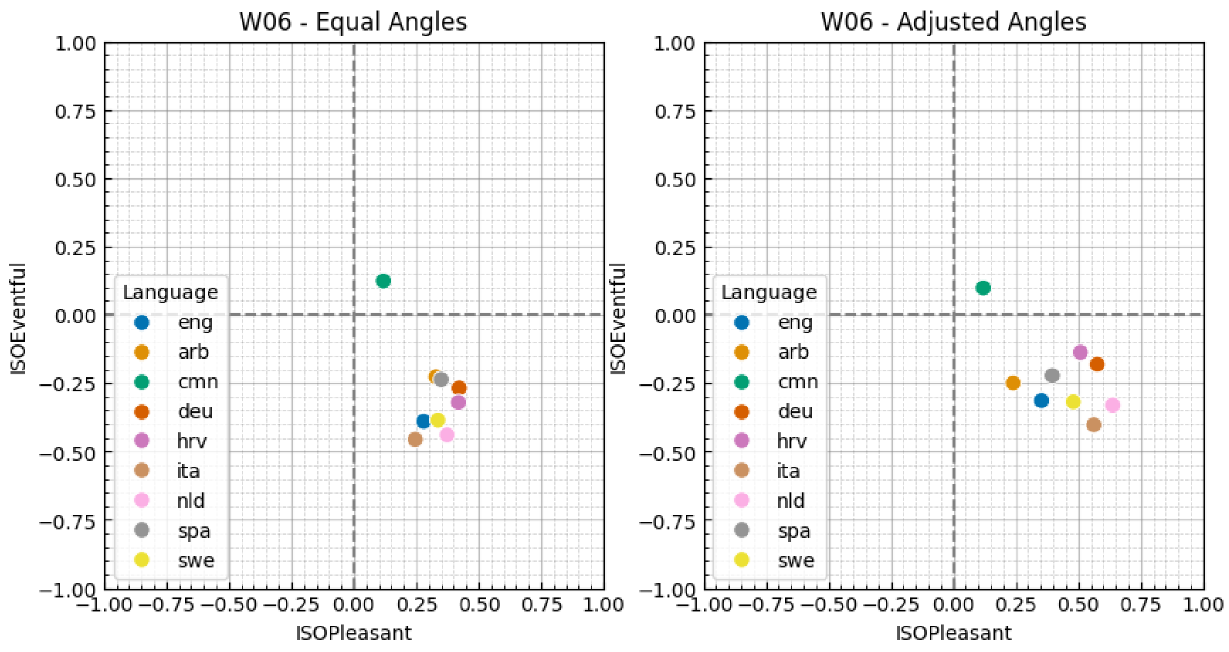
```
import soundscapy as sspy


def adj_angle_iso_coords(data: pd.DataFrame, angles, scale=100):
    isopl = data.apply(
        lambda x: adj_iso_pl(x[scales].values, angles, scale=scale), axis=1
    )
    isoev = data.apply(
        lambda x: adj_iso_ev(x[scales].values, angles, scale=scale), axis=1
    )
    return isopl, isoev


def adj_iso_pl(values, angles, scale=None):
    # scale = range of input values (e.g. 0-100)
    # The scaling factor was derived by comparing to
    # the scaling from the ISO method. Confirmed to be
    # the same value when using equal angles.
    # 100 * sum of abs values of the loading factors / 2
    iso_pl = np.sum(
        [np.cos(np.deg2rad(angle)) * values[i] for i, angle in enumerate(angles)]
    )
    if scale:
        iso_pl = iso_pl / (
            scale / 2 * np.sum(np.abs([np.cos(np.deg2rad(angle)) for angle in angles]))
        )
    return iso_pl


def adj_iso_ev(values, angles, scale=None):
    iso_ev = np.sum(
        [np.sin(np.deg2rad(angle)) * values[i] for i, angle in enumerate(angles)]
    )
    if scale:
        iso_ev = iso_ev / (
            scale / 2 * np.sum(np.abs([np.sin(np.deg2rad(angle)) for angle in angles]))
        )
    return iso_ev
```

```
fig, axes = plt.subplots(2, 2, figsize=(10, 10))
for i, rec in enumerate(["CG01", "CG04", "W06", "W09"]):
    cg01 = satp.query("Recording == @rec")
    cg01_res = {}
    for lang in cg01.Language.unique():
        cg01_lang = cg01.query("Language == @lang")
        isopl, isoev = adj_angle_iso_coords(cg01_lang, angles=ang_dict[lang])
        cg01_res[lang] = {
            "Language": lang,
            "ISOPleasant": np.mean(isopl),
            "ISOEventful": np.mean(isoev),
        }
        # print(np.mean(isopl), np.mean(isoev))
    cg01_res = pd.DataFrame.from_dict(cg01_res, orient="index")
    sspy.plotting.scatter(
        cg01_res, hue="Language", s=50, title=rec, ax=axes.flatten()[i]
    )
```



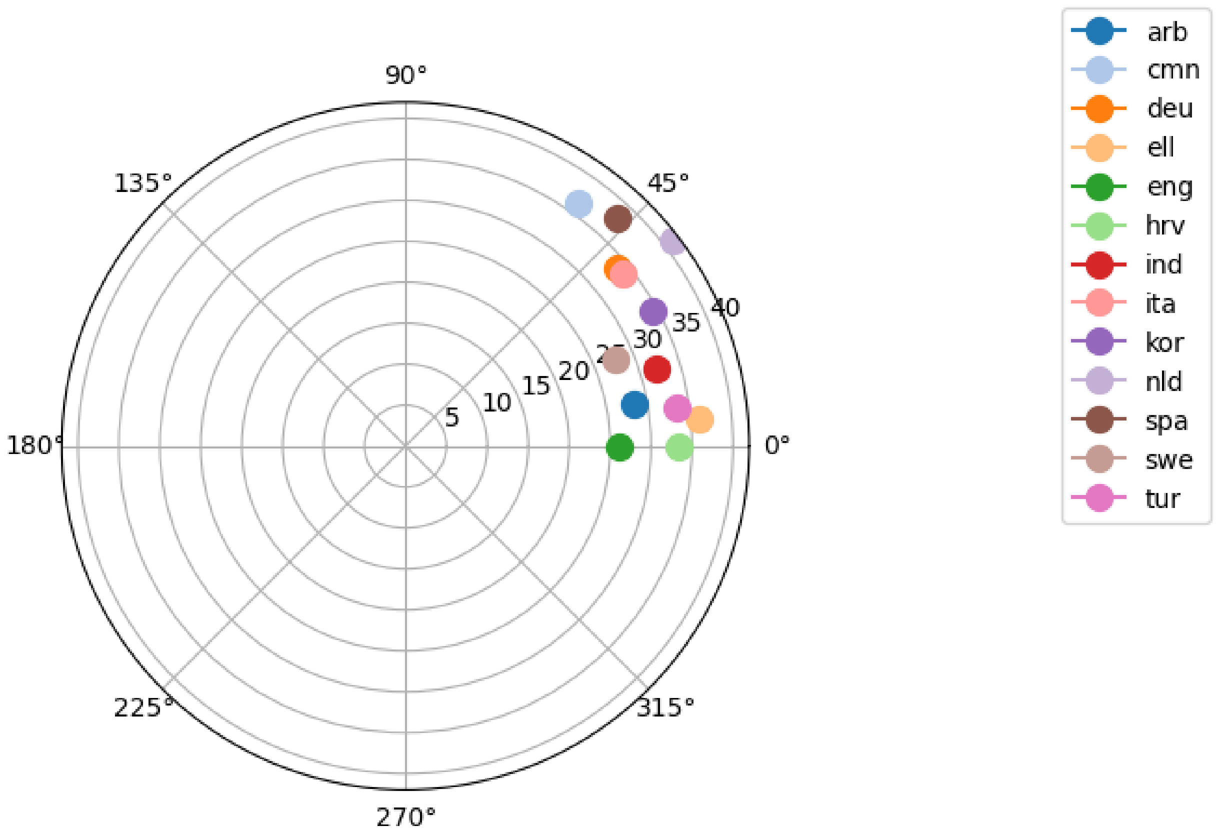
```python
fig, axes = plt.subplots(1, 2, figsize=(10, 5))
cg04 = satp.query("Recording == 'W06'")

cg04_res = {}
for lang in passing:
    cg04_lang = cg04.query("Language == @lang")
    isopl, isoev = adj_angle_iso_coords(cg04_lang, angles=eq_angles)
    cg04_res[lang] = {
        "Language": lang,
        "ISOPleasant": np.mean(isopl),
        "ISOEventful": np.mean(isoev),
    }
    # print(np.mean(isopl), np.mean(isoev))
```

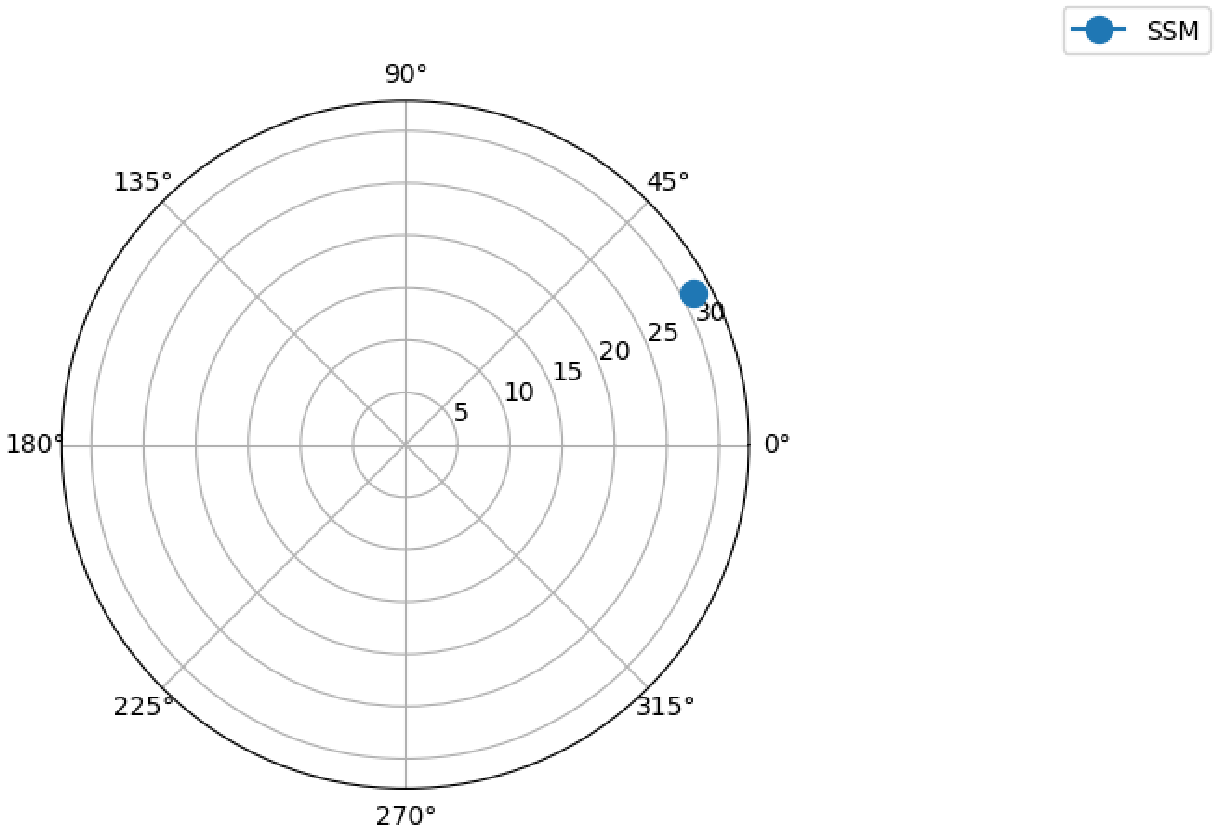
```python
cg04_res = pd.DataFrame.from_dict(cg04_res, orient="index")
sspy.plotting.scatter(
    cg04_res, hue="Language", s=70, title="W06 - Equal Angles", ax=axes.flatten()[0]
)

cg04_res = {}
for lang in passing:
    cg04_lang = cg04.query("Language == @lang")
    isopl, isoev = adj_angle_iso_coords(cg04_lang, angles=ang_dict[lang])
    cg04_res[lang] = {
        "Language": lang,
        "ISOPleasant": np.mean(isopl),
        "ISOEventful": np.mean(isoev),
    }
    # print(np.mean(isopl), np.mean(isoev))
cg04_res = pd.DataFrame.from_dict(cg04_res, orient="index")
sspy.plotting.scatter(
    cg04_res, hue="Language", s=70, title="W06 - Adjusted Angles", ax=axes.flatten()[1]
)
```



```python
cg01_res = circumplex.ssm_analyse(
    satp.query("Recording == 'CG01'"),
    scales,
    grouping=["Language"],
    grouped_angles=ang_dict,
)
cg01_all = circumplex.ssm_analyse(satp.query("Recording == 'CG01'"), scales)

cg01_res.plot()
plt.show()
```

```
cg01_all.plot()
plt.show()
```





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