# Exploring defining single value indices - SPI

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**Abstract**

This notebook contains several explorations and developments leading to the SPI framework.

## 1. Setup

### 1.1. Import Libraries

```
import soundscapy as sspy
import matplotlib.pyplot as plt
import pandas as pd
from pathlib import Path
import seaborn as sns
from scripts import msn_utils
import scripts.rpyskewnorm as snpy
import numpy as np
from scripts.MultiSkewNorm import MultiSkewNorm

import warnings

warnings.filterwarnings("ignore")
```

### 1.2. Load Data

In addition to loading the latest version of the ISD, we also exclude a few samples that were identified as survey outliers. Most notably, this includes the samples at RegentsParkFields which were impacted by helicopter flyovers.

```
# Load latest ISD dataset

data = sspy.isd.load()
data, excl_data = sspy.isd.validate(data)
data = data.query("Language != 'cmn'")

# Exclude RegentsParkJapan outliers
# excl_id = list(data.query("LocationID == 'RegentsParkJapan'").query("ISOEventful > 0.72 | ISOEventfu
# Excluded RegentsParkFields outliers
```

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```
# excl_id = excl_id + list(data.query("LocationID == 'RegentsParkFields' and ISOPleasant < 0").index)
excl_id = [652, 706, 548, 550, 551, 553, 569, 580, 609, 618, 623, 636, 643]
data.drop(excl_id, inplace=True)
data
```

| | LocationID | SessionID | GroupID | RecordID | start_time | end_time | latit |
|---|---|---|---|---|---|---|---|
| 0 | CarloV | CarloV2 | 2CV12 | 1434 | 2019-05-16 18:46:00 | 2019-05-16 18:56:00 | 37.1 |
| 1 | CarloV | CarloV2 | 2CV12 | 1435 | 2019-05-16 18:46:00 | 2019-05-16 18:56:00 | 37.1 |
| 2 | CarloV | CarloV2 | 2CV13 | 1430 | 2019-05-16 19:02:00 | 2019-05-16 19:12:00 | 37.1 |
| 3 | CarloV | CarloV2 | 2CV13 | 1431 | 2019-05-16 19:02:00 | 2019-05-16 19:12:00 | 37.1 |
| 4 | CarloV | CarloV2 | 2CV13 | 1432 | 2019-05-16 19:02:00 | 2019-05-16 19:12:00 | 37.1 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 1693 | Noorderplantsoen | Noorderplantsoen1 | NP161 | 61 | 2020-03-11 12:42:00 | 2020-03-11 12:55:00 | NaN |
| 1694 | Noorderplantsoen | Noorderplantsoen1 | NP162 | 63 | 2020-03-11 12:39:00 | 2020-03-11 13:00:00 | NaN |
| 1695 | Noorderplantsoen | Noorderplantsoen1 | NP162 | 62 | 2020-03-11 12:54:00 | 2020-03-11 12:58:00 | NaN |
| 1696 | Noorderplantsoen | Noorderplantsoen1 | NP162 | 64 | 2020-03-11 12:56:00 | 2020-03-11 12:59:00 | NaN |
| 1697 | Noorderplantsoen | Noorderplantsoen1 | NP163 | 70 | 2020-03-11 23:08:00 | 2020-03-11 23:18:00 | NaN |

#### *1.2.1. ISOCoordinate calculation according to Aletta et. al. (2024)*

To move the 8-item PAQ responses into the 2-dimensional circumplex space, we use the projection method first presented in ISO 12913-3:2018. This projection method and its associated formulae were recently updated further in Aletta et al. (2024) to include a correction for the language in which the survey was conducted. The formulae are as follows:

$$P_{ISO} = \frac{1}{\lambda_{pl}} \sum_{i=1}^{8} \cos\theta_i \cdot \sigma_i E_{ISO} = \frac{1}{\lambda_{pl}} \sum_{i=1}^{8} \sin\theta_i \cdot \sigma_i$$

where \$PAQ_i\$ is the response to the (i)th item of the PAQ. The resulting (x) and (y) values are then used to calculate the polar angle ( ) and the radial distance (r) as follows:

```
from soundscapy.surveys.survey_utils import LANGUAGE_ANGLES, PAQ_IDS

LANGUAGE_ANGLES
```

```
{'eng': (0, 46, 94, 138, 177, 241, 275, 340),
 'arb': (0, 36, 45, 135, 167, 201, 242, 308),
 'cmn': (0, 18, 38, 154, 171, 196, 217, 318),
 'hrv': (0, 84, 93, 160, 173, 243, 273, 354),
 'nld': (0, 43, 111, 125, 174, 257, 307, 341),
 'deu': (0, 64, 97, 132, 182, 254, 282, 336),
 'ell': (0, 72, 86, 133, 161, 233, 267, 328),
 'ind': (0, 53, 104, 123, 139, 202, 284, 308),
 'ita': (0, 57, 104, 143, 170, 274, 285, 336),
 'spa': (0, 41, 103, 147, 174, 238, 279, 332),
 'swe': (0, 66, 87, 146, 175, 249, 275, 335),
 'tur': (0, 55, 97, 106, 157, 254, 289, 313)}
```

```
tab = pd.DataFrame.from_dict(LANGUAGE_ANGLES, orient="index", columns=PAQ_IDS)
tab
```

Table 2: Language-specific angles for projection into the ISO 12913-3:2018 circumplex space.

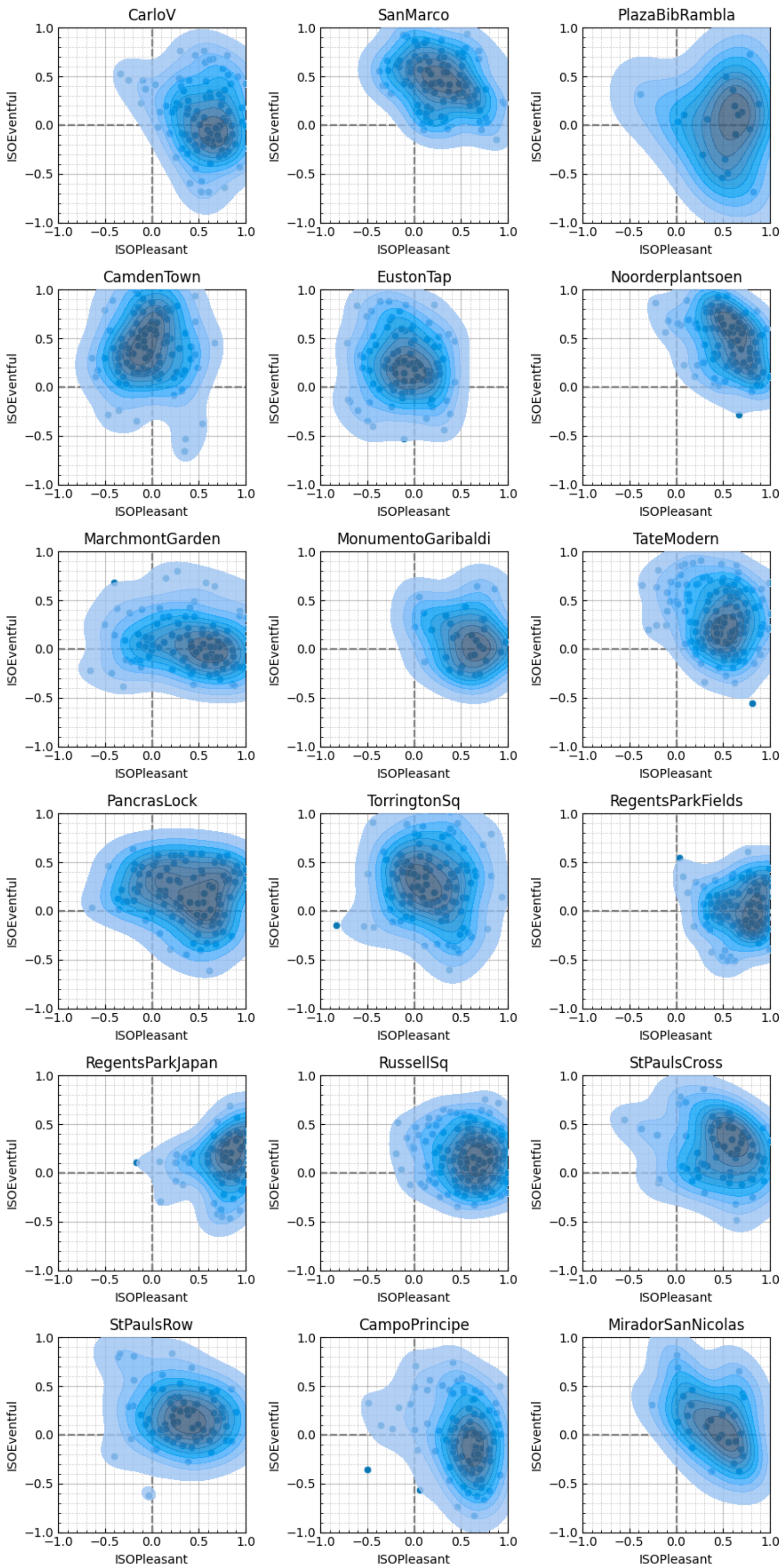
| | PAQ1 | PAQ2 | PAQ3 | PAQ4 | PAQ5 | PAQ6 | PAQ7 | PAQ8 |
|---|---|---|---|---|---|---|---|---|
| eng | 0 | 46 | 94 | 138 | 177 | 241 | 275 | 340 |
| arb | 0 | 36 | 45 | 135 | 167 | 201 | 242 | 308 |
| cmn | 0 | 18 | 38 | 154 | 171 | 196 | 217 | 318 |
| hrv | 0 | 84 | 93 | 160 | 173 | 243 | 273 | 354 |
| nld | 0 | 43 | 111 | 125 | 174 | 257 | 307 | 341 |
| deu | 0 | 64 | 97 | 132 | 182 | 254 | 282 | 336 |
| ell | 0 | 72 | 86 | 133 | 161 | 233 | 267 | 328 |
| ind | 0 | 53 | 104 | 123 | 139 | 202 | 284 | 308 |
| ita | 0 | 57 | 104 | 143 | 170 | 274 | 285 | 336 |
| spa | 0 | 41 | 103 | 147 | 174 | 238 | 279 | 332 |
| swe | 0 | 66 | 87 | 146 | 175 | 249 | 275 | 335 |
| tur | 0 | 55 | 97 | 106 | 157 | 254 | 289 | 313 |

```python
from soundscapy.surveys.survey_utils import PAQ_IDS

for i, row in data.iterrows():
    lang = row["Language"]
    angles = LANGUAGE_ANGLES[lang]
    iso_pl, iso_ev = (
        sspy.surveys.processing._adj_iso_pl(row[PAQ_IDS], angles, scale=4),
        sspy.surveys.processing._adj_iso_ev(row[PAQ_IDS], angles, scale=4),
    )
    data.loc[i, "ISOPleasant"] = iso_pl
    data.loc[i, "ISOEventful"] = iso_ev

data_list = [
    sspy.isd.select_location_ids(data, loc) for loc in data["LocationID"].unique()
]
fig = sspy.plotting.create_circumplex_subplots(
    data_list,
    plot_type="density",
    nrows=6,
    ncols=3,
    figsize=(9, 18),
    legend=True,
    incl_scatter=True,
    subtitles=[loc for loc in data["LocationID"].unique()],
    title="",
)

fig.tight_layout()
```

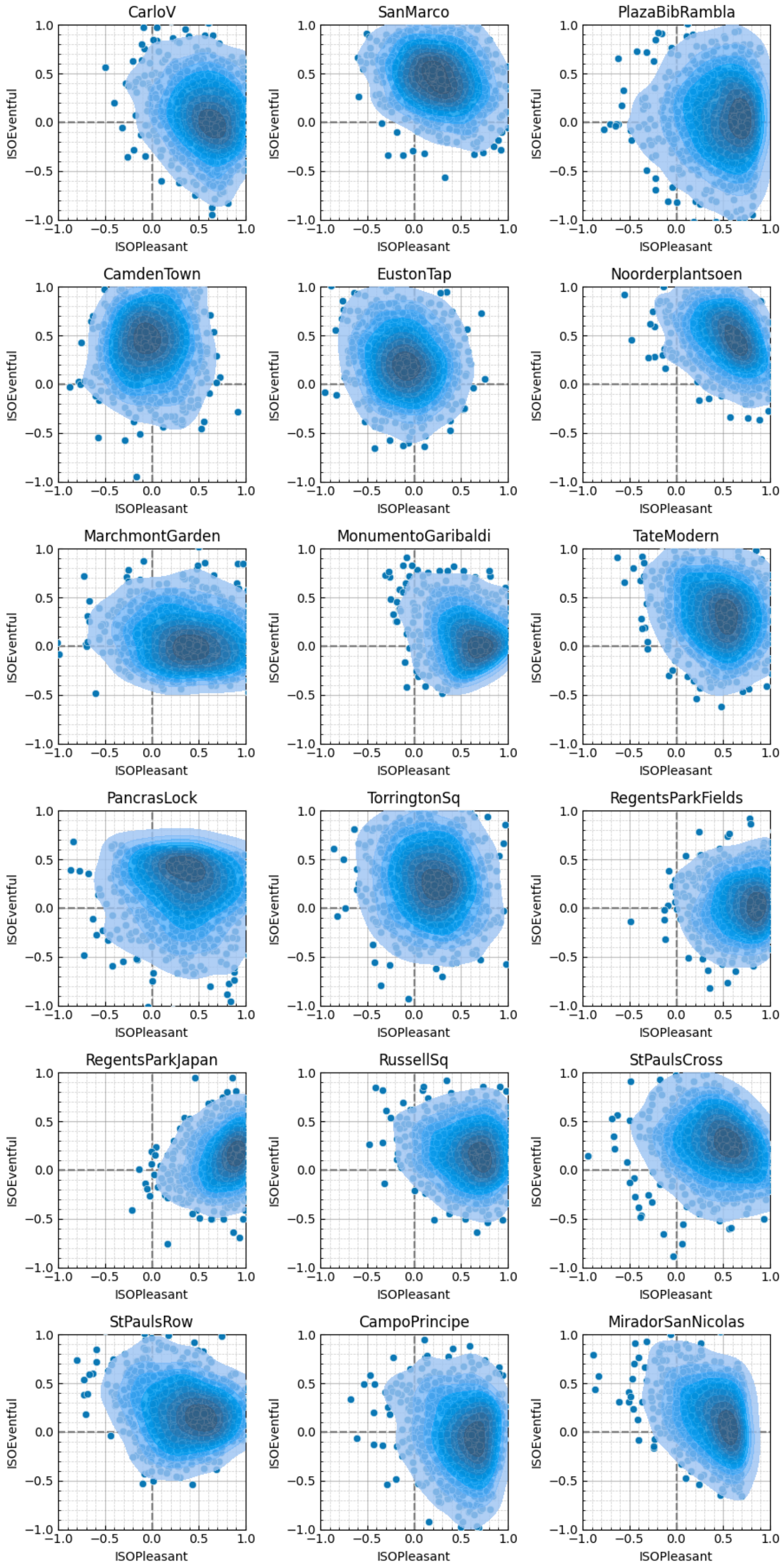

CarloV
SanMarco
PlazaBibRambla
CamdenTown
EustonTap
Noorderplantsoen
MarchmontGarden
MonumentoGaribaldi
TateModern
PancrasLock
TorringtonSq
RegentsParkFields
RegentsParkJapan
RussellSq
StPaulsCross
StPaulsRow
CampoPrincipe
MiradorSanNicolas
ISOEventful
ISOPleasant
−1.0
−0.5
0.0
0.5
1.0

```python
# Plotting distribution density with empirical scatter
def empirical_msn_scatter(data, loc):
    loc_msn = MultiSkewNorm()
    loc_msn.fit(
        data=data.query(f"LocationID == '{loc}'")[["ISOPleasant", "ISOEventful"]]
    )
    loc_msn.sample(1000)
    loc_Y = pd.DataFrame(loc_msn.sample_data, columns=["ISOPleasant", "ISOEventful"])
    return loc_Y


data_list = [empirical_msn_scatter(data, loc) for loc in data["LocationID"].unique()]

fig = sspy.plotting.create_circumplex_subplots(
    data_list,
    plot_type="density",
    nrows=6,
    ncols=3,
    figsize=(9, 18),
    legend=True,
    incl_scatter=True,
    subtitles=[loc for loc in data["LocationID"].unique()],
    title="",
)

fig.tight_layout()
```


CarloV
SanMarco
PlazaBibRambla
CamdenTown
EustonTap
Noorderplantsoen
MarchmontGarden
MonumentoGaribaldi
TateModern
PancrasLock
TorringtonSq
RegentsParkFields
RegentsParkJapan
RussellSq
StPaulsCross
StPaulsRow
CampoPrincipe
MiradorSanNicolas
ISOEventful
ISOPleasant
−1.0
−0.5
0.0
0.5
1.0

*1.3. The Soundscape Perception Index (SPI)*

The SPI works by assessing the assessed (or calculated) distribution of soundscape responses against a target distribution. This target distribution represents the goal for the soundscape design. Since we consider a location's soundscape perception to be the collective perception of its users, it is crucial that the target includes both the central tendency and the distribution.

*1.3.1. Note: Distributions in the circumplex*

We should begin by discussing how soundscape circumplex distributions are defined. The circumplex is defined by two axes: $P_{ISO}$ and $E_{ISO}$ which are limited to the range $[-1, 1]$. Typically the distribution of collective perception of a soundscape is also not symmetrical, therefore making it a skewed distribution. A soundscape distribution is thus a two-dimensional truncated skew-normal distribution.

The skew-normal distribution is defined by three parameters: location, scale and shape. The location parameter defines the centre of the distribution, the scale parameter defines the spread of the distribution, and the shape parameter defines the skew of the distribution. The skew-normal distribution is defined as:

$$f(x; a, \omega, \alpha) = \frac{2}{\omega}\phi\left(\frac{x-a}{\omega}\right)\Phi\left(\alpha\frac{x-a}{\omega}\right)$$

where $\phi$ and $\Phi$ are the standard normal probability density function and cumulative distribution function respectively. The skew-normal distribution is thus a generalisation of the normal distribution, with the shape parameter $\alpha$ defining the skew. A positive shape parameter results in a right-skewed distribution, and a negative shape parameter results in a left-skewed distribution.

Truncated skew-normal distribution: https://www-tandfonline-com.libproxy.ucl.ac.uk/doi/epdf/10.1080/03610910902936

To generate the truncated skew-normal distribution, we use rejection sampling. This is a method of generating a distribution by sampling from a simpler distribution and rejecting samples that do not fit the target distribution. In this case, we sample from a skew-normal distribution (`scipy.stats.skewnorm`) and reject samples that are outside of the range $[-1, 1]$.

*1.3.1.1. Example - Calculating the moments of location's distribution and generating the equivalent distribution using rejection sampling.*

```
test_loc = "SanMarco"
test_data = sspy.isd.select_location_ids(data, test_loc)

msn = MultiSkewNorm()
msn.fit(data=test_data[["ISOPleasant", "ISOEventful"]])

msn.summary()
```

```
Fitted from data. n = 96
Direct Parameters:
xi:    [[0.06  0.597]]
omega: [[ 0.15  -0.058]
 [-0.058  0.093]]
alpha: [ 0.868 -0.561]


Centred Parameters:
mean:  [[0.281 0.447]]
sigma: [[ 0.101 -0.025]
 [-0.025  0.07 ]]
```

```
skew:  [ 0.145 -0.078]
```

```
Y = msn.sample(1000, return_sample=True)
Y = pd.DataFrame(Y, columns=["ISOPleasant", "ISOEventful"])
D, p = msn.ks2ds(test_data[["ISOPleasant", "ISOEventful"]])

color = sns.color_palette("colorblind", 1)[0]

fig, axes = plt.subplots(1, 2, figsize=(12, 6))
sspy.density_plot(
    test_data,
    ax=axes[0],
    density_type="full",
    title=f"a) Empirical data",
    color=color,
)
sspy.density_plot(
    Y,
    ax=axes[1],
    density_type="full",
    title="b) MSN sampled distribution\n n sample = 1000",
    color=color,
)
plt.tight_layout()
```

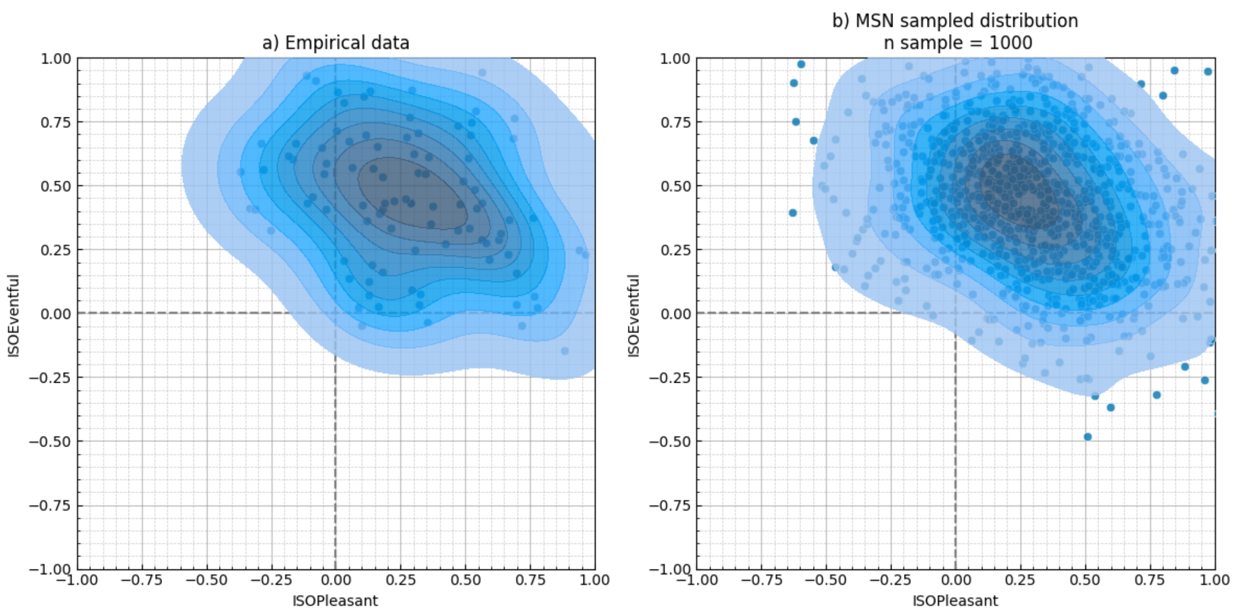



Figure 1: Example of fitting and sampling from a multivariate skew-normal distribution for data from the Piazza San Marco location.

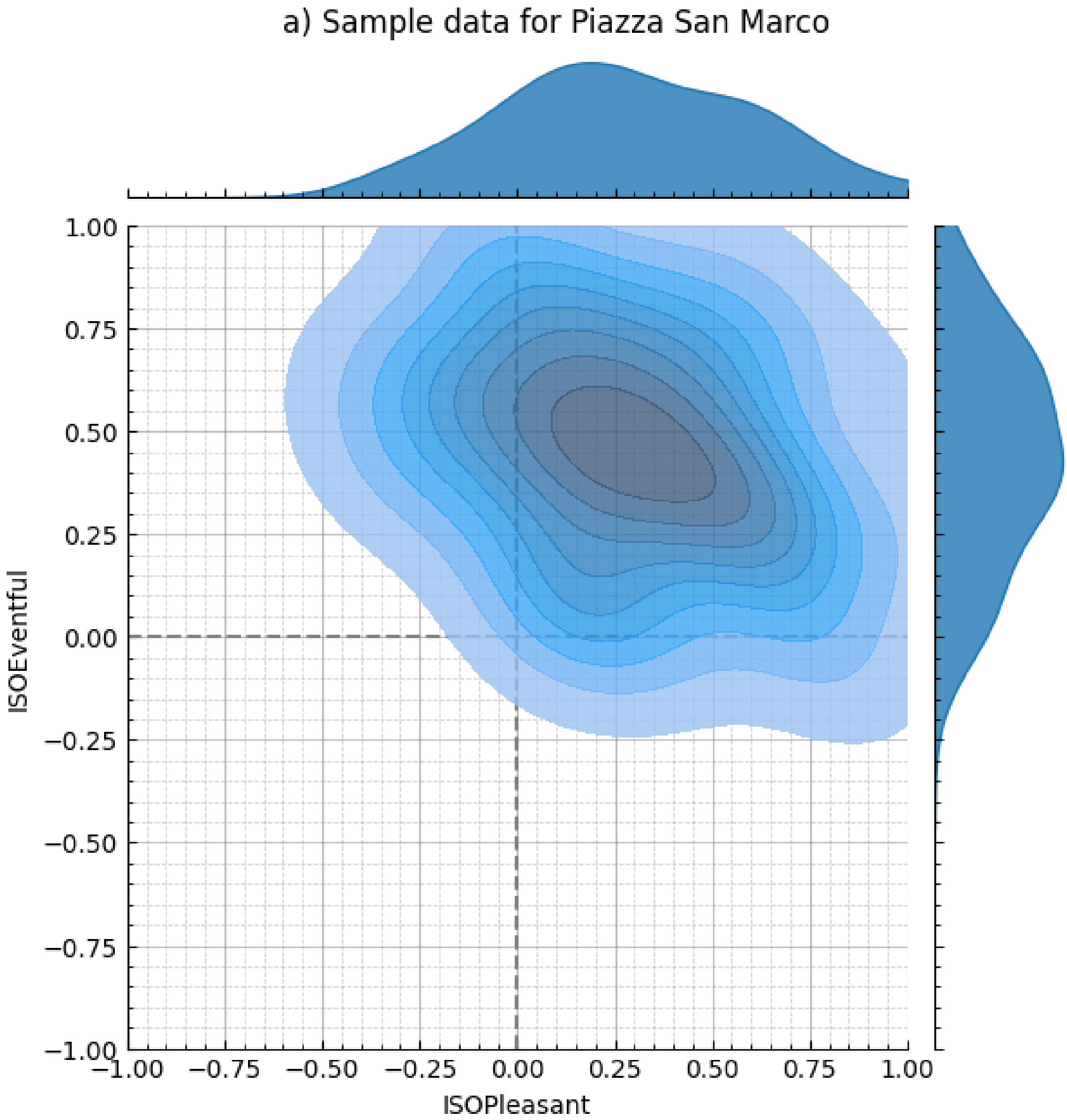
```
# Hack using alpha dev version of soundscapy
from soundscapy.plotting.circumplex_plot import (
    CircumplexPlot,
    Backend,
```

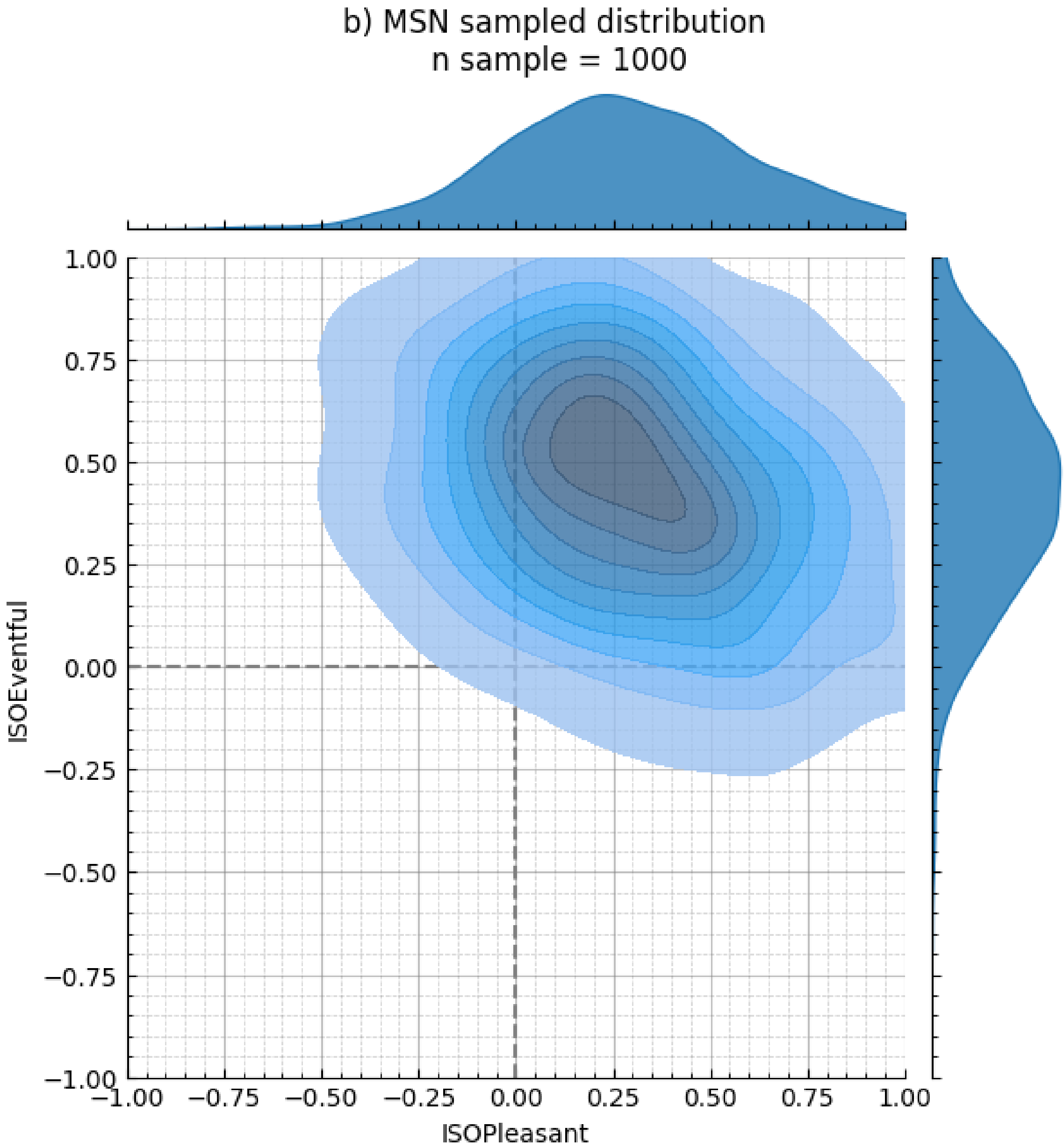
```
    CircumplexPlotParams,
)

Y = msn.sample(1000, return_sample=True)
Y = pd.DataFrame(Y, columns=["ISOPleasant", "ISOEventful"])
D, p = msn.ks2ds(test_data[["ISOPleasant", "ISOEventful"]])

params = CircumplexPlotParams(title="a) Sample data for Piazza San Marco")
plot = CircumplexPlot(test_data, params, backend=Backend.SEABORN)
g = plot.jointplot()
g.get_figure()[0].suptitle("a) Sample data for Piazza San Marco", y=1.02)
g.show()

params = CircumplexPlotParams(title="b) MSN sampled distribution\n n sample = 1000")
plot = CircumplexPlot(Y, params, backend=Backend.SEABORN)
g = plot.jointplot()
g.get_figure()[0].suptitle("b) MSN sampled distribution\n n sample = 1000", y=1.05)
g.show()
```


a) Sample data for Piazza San Marco
ISOEventful
ISOPleasant
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00




```
# Universal pleasant target
target_1 = MultiSkewNorm()
target_1.define_dp(
    xi=np.array([0.5, 0.0]),
    omega=np.array([[0.2, 0], [0, 0.2]]),
    alpha=np.array([1, 0]),
)
target_2 = MultiSkewNorm()
target_2.define_dp(
    xi=np.array([[1.0, -0.4]]),
    omega=np.array([[0.17, -0.04], [-0.04, 0.09]]),
```

```
    alpha=np.array([-8, 1]),
)

target_3 = MultiSkewNorm()
target_3.define_dp(
    xi=np.array([0.5, 0.7]),
    omega=np.array([[0.1, 0.05], [0.05, 0.1]]),
    alpha=np.array([0, -5]),
)

Y_1 = target_1.sample(1000, return_sample=True)
Y_1 = pd.DataFrame(Y_1, columns=["ISOPleasant", "ISOEventful"])
Y_2 = target_2.sample(1000, return_sample=True)
Y_2 = pd.DataFrame(Y_2, columns=["ISOPleasant", "ISOEventful"])
Y_3 = target_3.sample(1000, return_sample=True)
Y_3 = pd.DataFrame(Y_3, columns=["ISOPleasant", "ISOEventful"])
```

```
fig, axes = plt.subplots(1, 3, figsize=(18, 6))
sspy.density_plot(
    Y_1,
    ax=axes[0],
    title="a) Target 1",
    color="red",
)
sspy.density_plot(Y_2, ax=axes[1], title="b) Target 2", color="red")
sspy.density_plot(Y_3, ax=axes[2], title="c) Target 3", color="red")
plt.tight_layout()
plt.show()
```

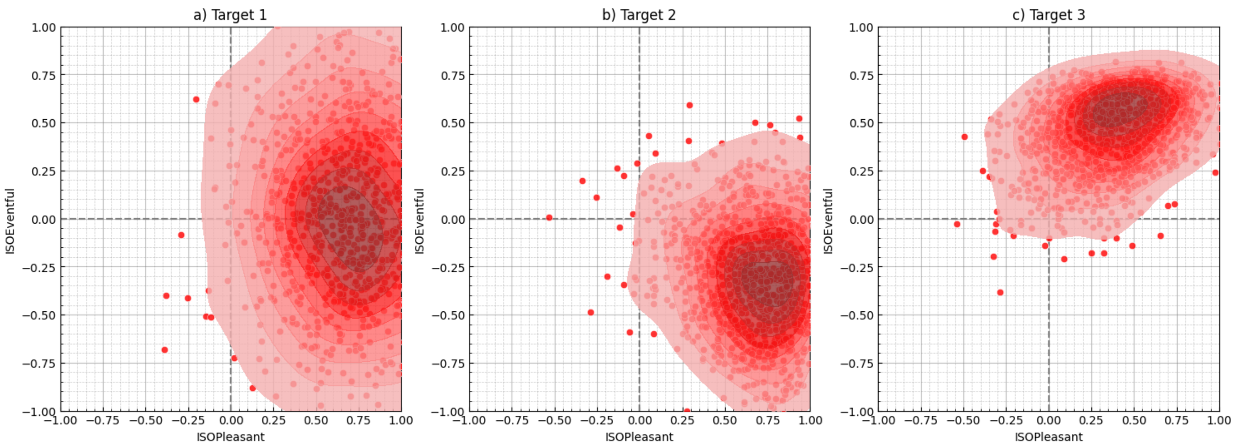



Figure 2: Example of defining and sampling from three arbitrary bespoke targets.

```
D_1 = msn_utils.ks2d2s(
    test_data=test_data[["ISOPleasant", "ISOEventful"]], target_data=Y_1, extra=True
)
D_2 = msn_utils.ks2d2s(
    test_data=test_data[["ISOPleasant", "ISOEventful"]], target_data=Y_2, extra=True
```

```python
)
D_3 = msn_utils.ks2d2s(
    test_data=test_data[["ISOPleasant", "ISOEventful"]], target_data=Y_3, extra=True
)
```

```python
from IPython.display import Markdown
from tabulate import tabulate

D_tbl = [
    ["tgt_1", D_1[1].round(2), D_1[0]],
    ["tgt_2", D_2[1].round(2), D_2[0]],
    ["tgt_3", D_3[1].round(2), D_2[0]],
]
Markdown(tabulate(D_tbl, headers=["Target", "D", "p"], tablefmt="grid"))
```

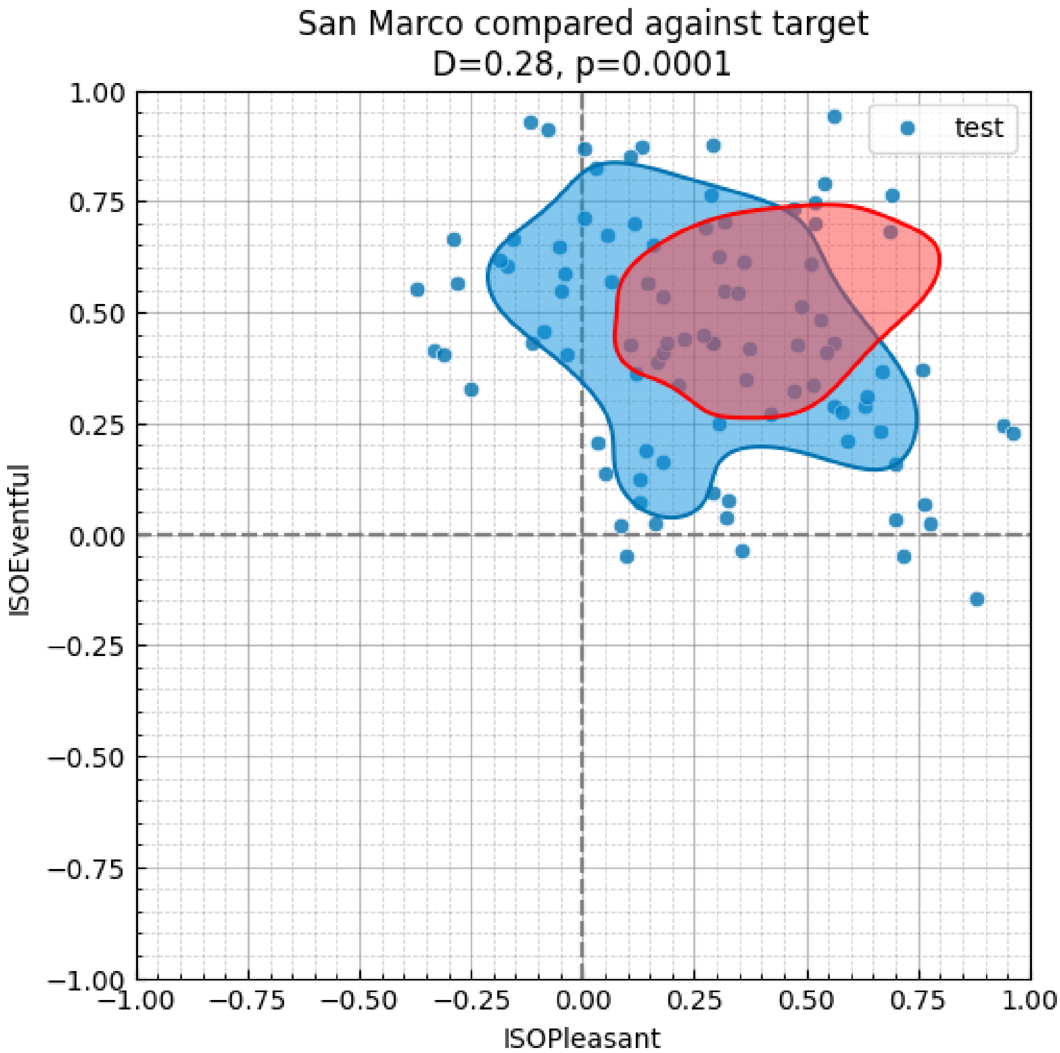
Table 3: Kolmogorov-Smirnov test comparing the empirical test distribution (Piazza San Marco) against three soundscape target distributions.

| Target | D | p |
|---|---|---|
| tgt_1 | 0.66 | 6.94745e-25 |
| tgt_2 | 0.83 | 8.96388e-39 |
| tgt_3 | 0.28 | 8.96388e-39 |

```python
fig, ax = plt.subplots(figsize=(6, 6))

sspy.density_plot(
    sspy.isd.select_location_ids(data, "SanMarco"),
    ax=ax,
    simple_density=True,
    label="test",
    incl_scatter=True,
    incl_outline=True,
    color=sns.palettes.color_palette("colorblind", 1)[0],
)

sspy.density_plot(
    pd.DataFrame(
        {
            "ISOPleasant": target_3.sample_data[:, 0],
            "ISOEventful": target_3.sample_data[:, 1],
        }
    ),
    ax=ax,
    incl_scatter=False,
    incl_outline=True,
    simple_density=True,
    label="target",
    title=f"San Marco compared against target\nD={D_3[1].round(2)}, p={D_3[0].round(4)}",
    color="red",
)
```




```
spis = {}
for location in data.LocationID.unique():
    loc_data = sspy.isd.select_location_ids(data, location)[
        ["ISOPleasant", "ISOEventful"]
    ]
    spi_res = [msn_utils.spi(loc_data, target_data) for target_data in [Y_1, Y_2, Y_3]]
    spis[location] = spi_res
spis_df = pd.DataFrame(spis).T
spis_df.columns = ["tgt_1", "tgt_2", "tgt_3"]
# spis_df
```

```
def table_fill(spis_df, idx):
    tgt_1_order = spis_df["tgt_1"].sort_values(ascending=False)
    tgt_2_order = spis_df["tgt_2"].sort_values(ascending=False)
    tgt_3_order = spis_df["tgt_3"].sort_values(ascending=False)

    def tgt_str(tgt_order, idx):
```

```python
        return f"{tgt_order.values[idx]}   {tgt_order.index[idx]}"

    return [
        f"{idx+1}",
        tgt_str(tgt_1_order, idx),
        tgt_str(tgt_2_order, idx),
        tgt_str(tgt_3_order, idx),
    ]
```

```python
spis_tbl = [table_fill(spis_df, idx) for idx in range(len(spis_df))]
tabulate.PRESERVE_WHITESPACE = True
Markdown(
    tabulate(
        spis_tbl,
        headers=[
            "Ranking",
            "$SPI_1$ (pleasant)",
            "$SPI_2$ (calm)",
            "$SPI_3$ (vibrant)",
        ],
        tablefmt="pipe",
    )
)
```

Table 4: SPI scores and rankings for the soundscapes of locations included in the International Soundscape Database (ISD).

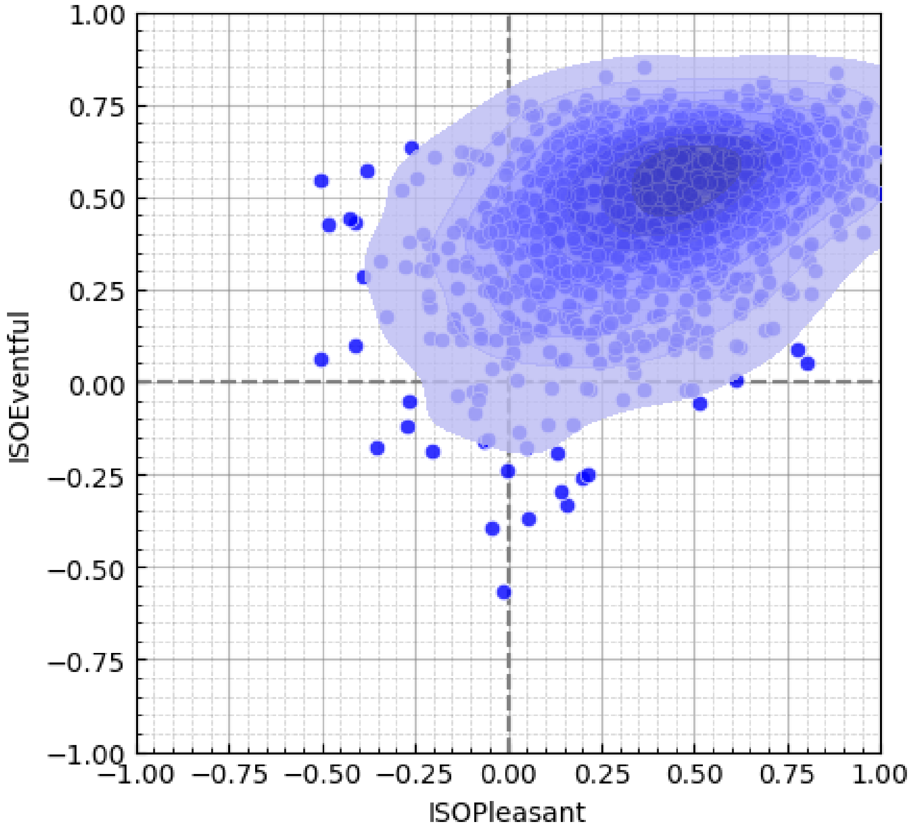
| Ranking | $SPI_1$ (pleasant) | $SPI_2$ (calm) | $SPI_3$ (vibrant) |
|---:|---|---|---|
| 1 | 70 RegentsParkFields | 61 CampoPrincipe | 71 SanMarco |
| 2 | 69 CarloV | 52 CarloV | 62 TateModern |
| 3 | 65 RegentsParkJapan | 50 PlazaBibRambla | 60 StPaulsCross |
| 4 | 62 CampoPrincipe | 49 RegentsParkFields | 58 Noorderplantsoen |
| 5 | 61 PlazaBibRambla | 45 MarchmontGarden | 55 PancrasLock |
| 6 | 61 RussellSq | 44 MonumentoGaribaldi | 54 TorringtonSq |
| 7 | 61 MarchmontGarden | 40 RussellSq | 48 StPaulsRow |
| 8 | 61 MonumentoGaribaldi | 38 RegentsParkJapan | 48 RussellSq |
| 9 | 59 PancrasLock | 38 PancrasLock | 47 MiradorSanNicolas |
| 10 | 53 StPaulsCross | 32 MiradorSanNicolas | 43 CamdenTown |
| 11 | 49 TateModern | 30 TateModern | 40 CarloV |
| 12 | 48 StPaulsRow | 30 StPaulsCross | 36 MonumentoGaribaldi |
| 13 | 43 MiradorSanNicolas | 28 TorringtonSq | 34 MarchmontGarden |
| 14 | 38 Noorderplantsoen | 28 StPaulsRow | 33 PlazaBibRambla |
| 15 | 35 TorringtonSq | 17 SanMarco | 33 CampoPrincipe |
| 16 | 33 SanMarco | 16 Noorderplantsoen | 32 EustonTap |
| 17 | 21 CamdenTown | 15 CamdenTown | 27 RegentsParkFields |
| 18 | 15 EustonTap | 13 EustonTap | 27 RegentsParkJapan |

```python
spis_df["tgt_1"].sort_values(ascending=False)
```

```
RegentsParkFields      70
CarloV                 69
RegentsParkJapan       65
```

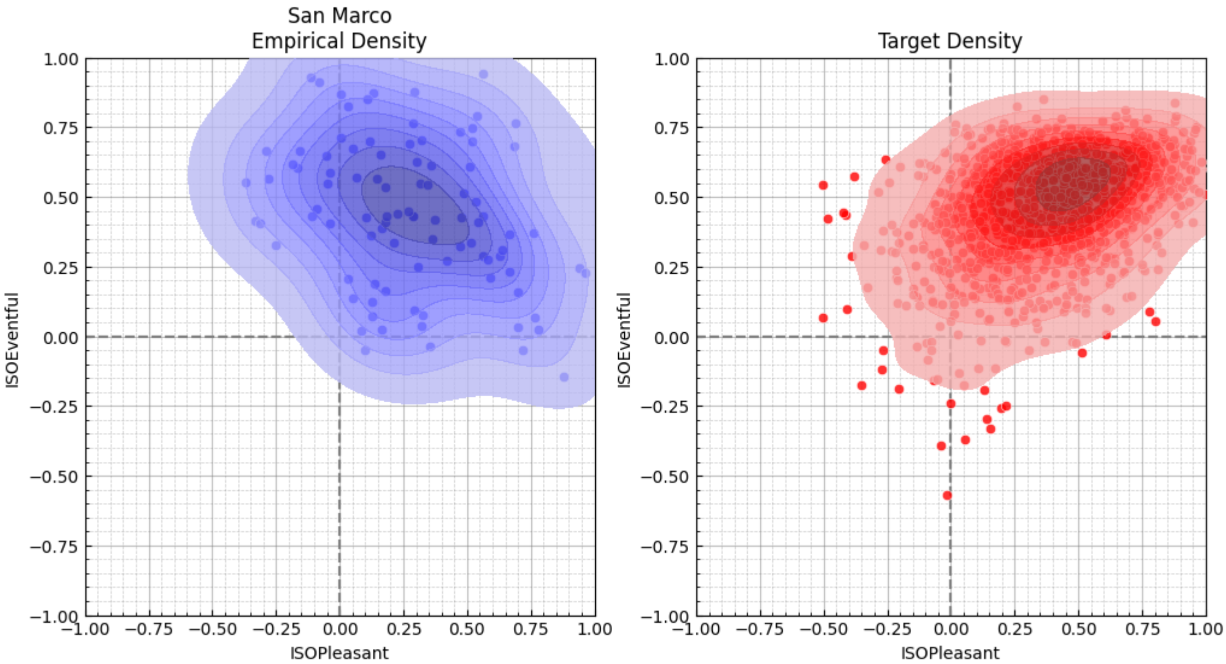
```
CampoPrincipe          62
PlazaBibRambla         61
RussellSq              61
MarchmontGarden        61
MonumentoGaribaldi     61
PancrasLock            59
StPaulsCross           53
TateModern             49
StPaulsRow             48
MiradorSanNicolas      43
Noorderplantsoen       38
TorringtonSq           35
SanMarco               33
CamdenTown             21
EustonTap              15
Name: tgt_1, dtype: int64
```

```
target = MultiSkewNorm()
target.define_dp(
    xi=np.array([0.5, 0.7]),
    omega=np.array([[0.1, 0.05], [0.05, 0.1]]),
    alpha=np.array([0, -5]),
)
target.sample(1000)
target.sspy_plot()
```




```
fig, axes = plt.subplots(1, 2, figsize=(12, 6))

sspy.density_plot(
    test_data,
    incl_scatter=True,
    title="San Marco\nEmpirical Density",
    ax=axes[0],
    color="blue",
)
sspy.density_plot(
    pd.DataFrame(target.sample_data, columns=["ISOPleasant", "ISOEventful"]),
    incl_scatter=True,
    title="Target Density",
    ax=axes[1],
    color="red",
)
```




Once the target is defined, we will generate a set of points that represent the target distribution.

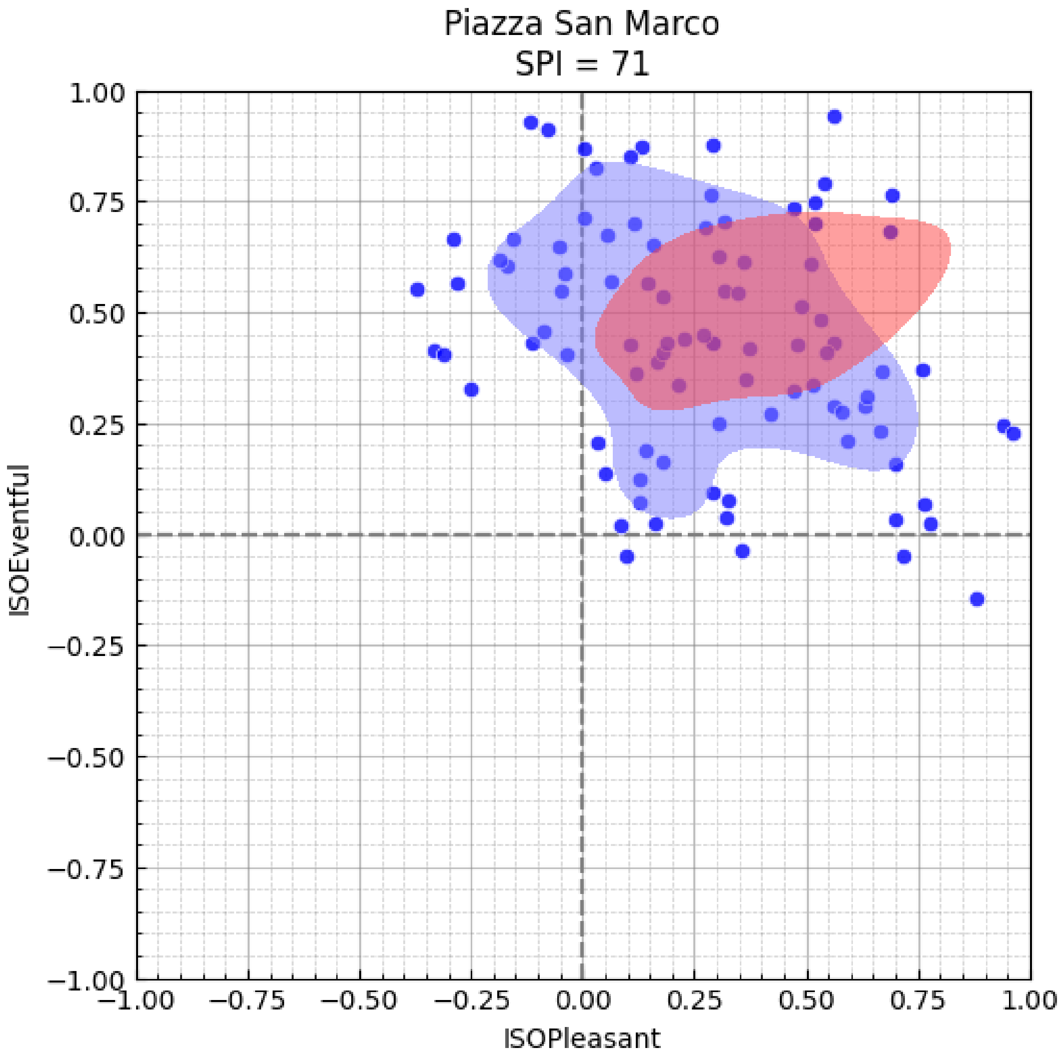
Now that our target has been defined, we can calculate the SPI for a given set of responses. We will use the responses from Piazza San Marco in Venice, Italy, as an example.

```
test_spi = target.spi(
    data.query("LocationID == 'SanMarco'")[["ISOPleasant", "ISOEventful"]]
)
print(f"San Marco SPI = {test_spi}")
```

```
San Marco SPI = 71
```

```
fig, ax = plt.subplots(figsize=(6, 6))

sspy.density_plot(
    sspy.isd.select_location_ids(data, "SanMarco"),
    ax=ax,
    simple_density=True,
    title=f"",
    color="blue",
)
sspy.density_plot(
    pd.DataFrame(target.sample_data, columns=["ISOPleasant", "ISOEventful"]),
    ax=ax,
    incl_scatter=False,
    simple_density=True,
    title=f"Piazza San Marco\nSPI = {test_spi}",
    color="red",
)
```

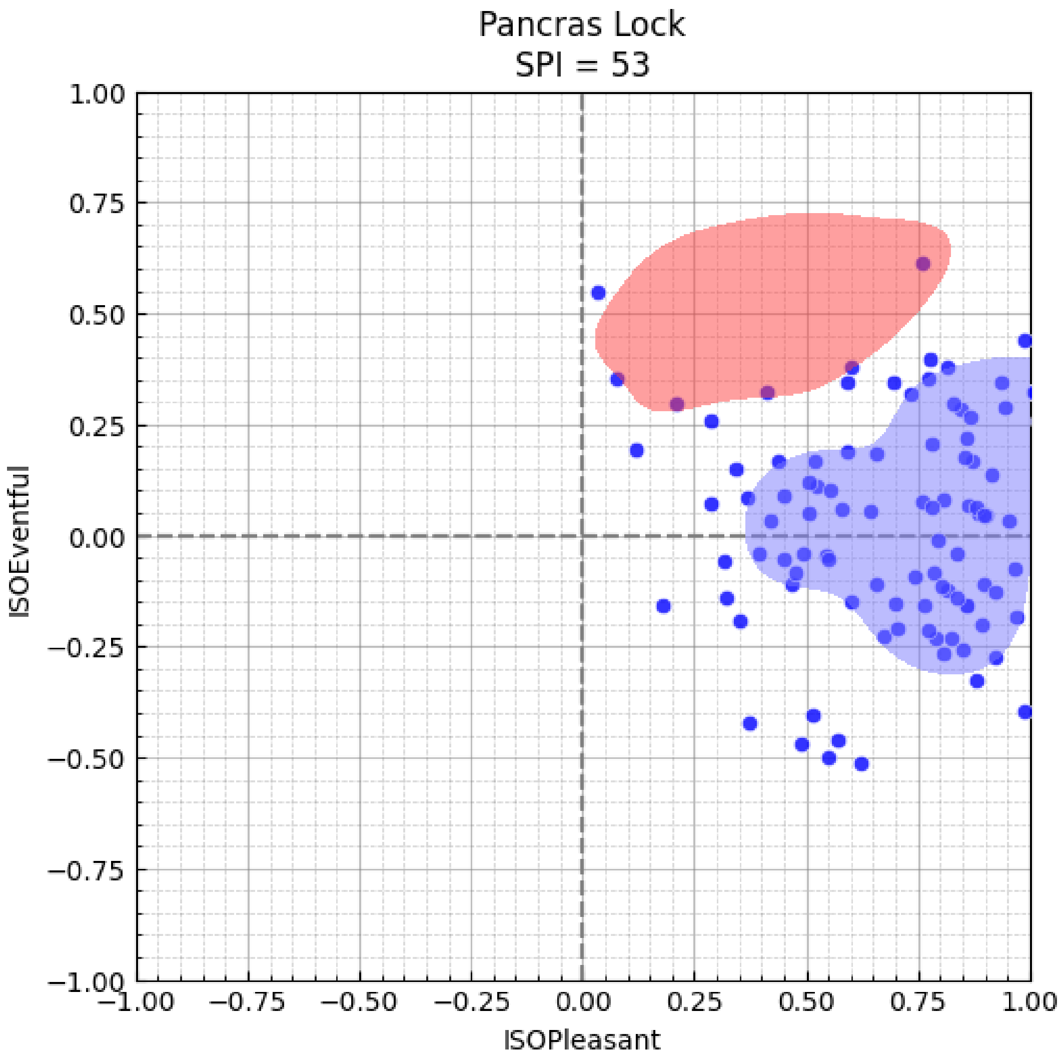



We can compare this against another location, such as St Pancras Lock.

```
test_spi = target.spi(
    sspy.isd.select_location_ids(data, "PancrasLock")[["ISOPleasant", "ISOEventful"]]
)
fig, ax = plt.subplots(figsize=(6, 6))

sspy.density_plot(
    sspy.isd.select_location_ids(data, "RegentsParkFields"),
    ax=ax,
    simple_density=True,
    title=f"",
    color="blue",
)
sspy.density_plot(
    pd.DataFrame(target.sample_data, columns=["ISOPleasant", "ISOEventful"]),
    ax=ax,
```

```
    incl_scatter=False,
    simple_density=True,
    title=f"Pancras Lock\nSPI = {test_spi}",
    color="red",
)
```




SPI scores assessed against a target should not inherently be considered a measure of the quality of the soundscape - instead it reflects the degree to which the soundscape matches the target. A high SPI score does not necessarily mean that the soundscape is of high quality, but rather that the soundscape is of high quality *according to the target*.

The $SPI_{bespoke}$ thus provides a method for scoring and ranking the success of a soundscape design against the designer's goals. Sticking with our defined target, we can assess all of the locations in the ISD and see which locations best match our target.

```
loc_bespoke = {}
for location in data.LocationID.unique():
    loc_bespoke[location] = target.spi(
```

```python
        sspy.isd.select_location_ids(data, location)[["ISOPleasant", "ISOEventful"]]
    )

loc_bespoke = pd.DataFrame.from_dict(loc_bespoke, orient="index", columns=["SPI"])
loc_bespoke.sort_values(by="SPI", ascending=False, inplace=True)
loc_bespoke
```

| | SPI |
|---|---|
| SanMarco | 71 |
| TateModern | 61 |
| Noorderplantsoen | 61 |
| StPaulsCross | 59 |
| TorringtonSq | 54 |
| PancrasLock | 53 |
| StPaulsRow | 47 |
| RussellSq | 46 |
| MiradorSanNicolas | 46 |
| CamdenTown | 43 |
| CarloV | 40 |
| MonumentoGaribaldi | 36 |
| MarchmontGarden | 35 |
| PlazaBibRambla | 35 |
| CampoPrincipe | 33 |
| EustonTap | 31 |
| RegentsParkJapan | 27 |
| RegentsParkFields | 25 |

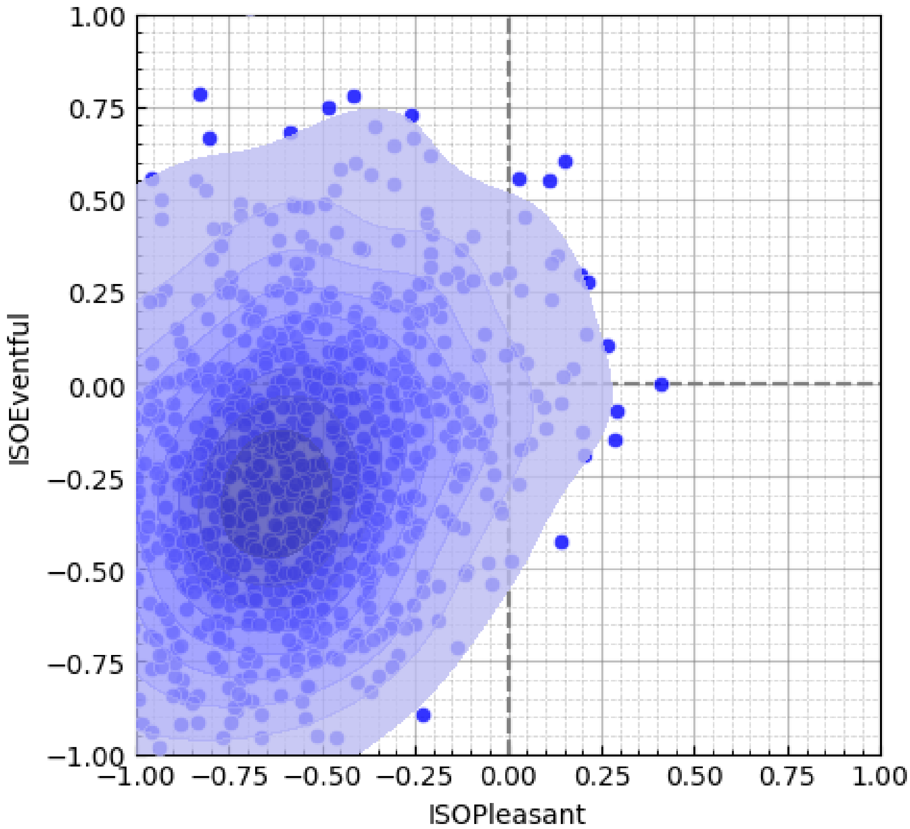
Assessed against a different target would result in a different ranking:

```python
target = MultiSkewNorm()
target.define_dp(
    np.array([-0.5, -0.5]),
    np.array([[0.1, 0], [0, 0.2]]),
    np.array([-0.85, 1.5]),
)
target.summary()

target.sample(n=1000)
target.sspy_plot()
```

```
Fitted from direct parameters.
Direct Parameters:
xi:    [-0.5 -0.5]
omega: [[0.1 0. ]
 [0.  0.2]]
alpha: [-0.85  1.5 ]


None
```




```python
loc_bespoke_2 = {}
for location in data.LocationID.unique():
    loc_bespoke_2[location] = target.spi(
        sspy.isd.select_location_ids(data, location)[["ISOPleasant", "ISOEventful"]]
    )

loc_bespoke_2 = pd.DataFrame.from_dict(loc_bespoke_2, orient="index", columns=["SPI"])
loc_bespoke_2.sort_values(by="SPI", ascending=False, inplace=True)
loc_bespoke_2
```

| | SPI |
|---|---|
| EustonTap | 30 |
| CamdenTown | 22 |
| MarchmontGarden | 19 |
| TorringtonSq | 19 |
| PancrasLock | 17 |
| PlazaBibRambla | 15 |
| StPaulsRow | 15 |
| CampoPrincipe | 11 |
| StPaulsCross | 11 |
| RegentsParkJapan | 8 |
| RussellSq | 8 |
| CarloV | 8 |

| | SPI |
|---|---|
| SanMarco | 8 |
| TateModern | 8 |
| MiradorSanNicolas | 6 |
| MonumentoGaribaldi | 5 |
| Noorderplantsoen | 4 |
| RegentsParkFields | 3 |

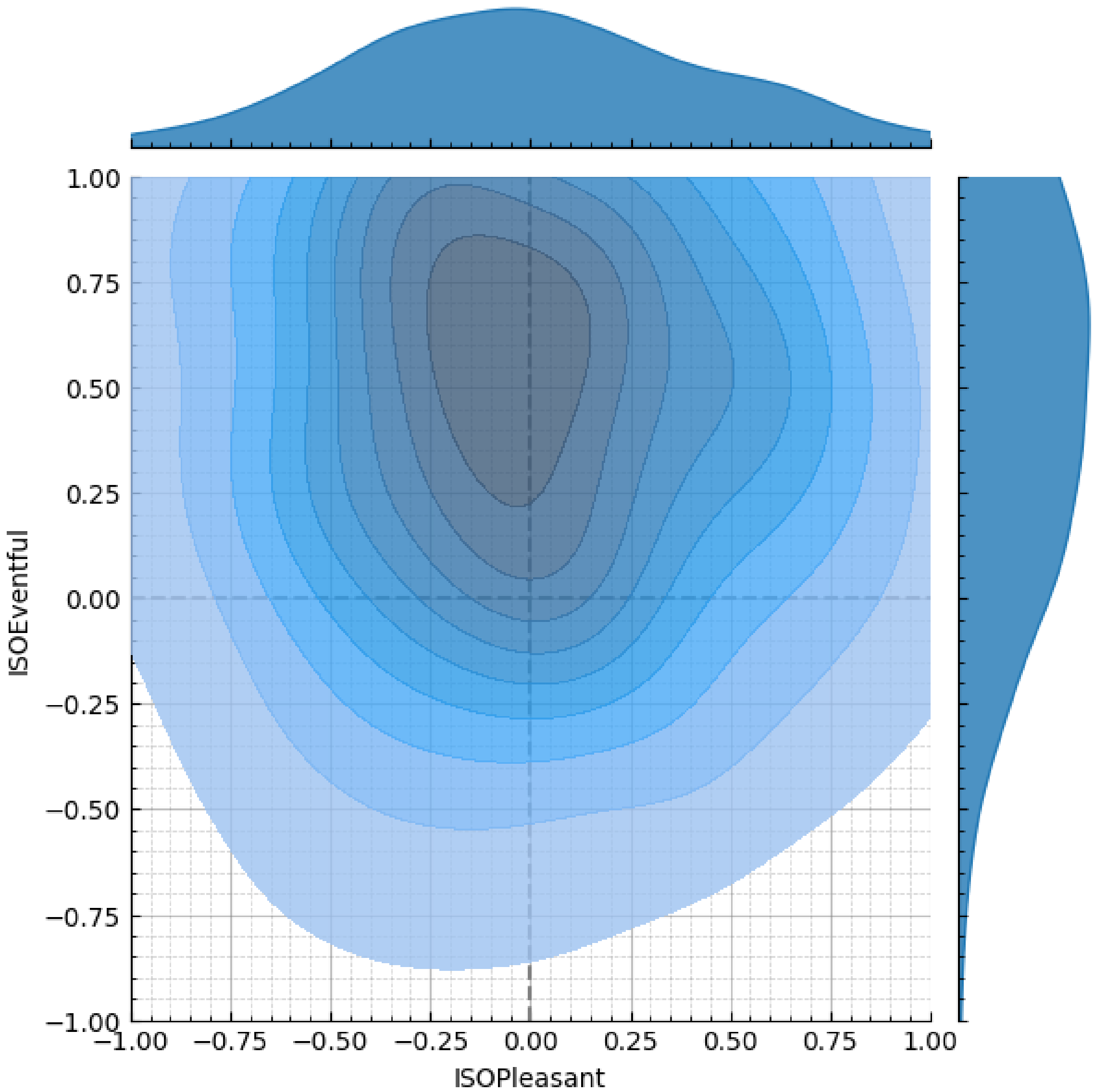
```
target1 = MultiSkewNorm()
target1.define_dp(
    np.array([-0.5, 0.5]), np.array([[0.1, 0], [0, 0.1]]), np.array([0, 0])
)
target1.sample()

target2 = MultiSkewNorm()
target2.define_dp(np.array([0.5, 0]), np.array([[0.1, 0], [0, 0.2]]), np.array([0, 0]))
target2.sample()

target_mix_y = target1.sample_data + target2.sample_data

target_mix_y = pd.DataFrame(target_mix_y, columns=["ISOPleasant", "ISOEventful"])

plot = CircumplexPlot(target_mix_y, backend=Backend.SEABORN)
g = plot.jointplot()
g.show()
```




## References

Aletta, F., Mitchell, A., Oberman, T., Kang, J., Khelil, S., Bouzir, T.A.K., Berkouk, D., Xie, H., Zhang, Y., Zhang, R., Yang, X., Li, M., Jambrošić, K., Zaninović, T., van den Bosch, K., Lühr, T., Orlik, N., Fitzpatrick, D., Sarampalis, A., Aumond, P., Lavandier, C., Moshona, C.C., Lepa, S., Fiebig, A., Papadakis, N.M., Stavroulakis, G.E., Sudarsono, A.S., Sarwono, S.J., Puglisi, G.E., Jafari, F., Astolfi, A., Shtrepi, L., Nagahata, K., Jo, H.I., Jeon, J.Y., Lam, B., Chieng, J., Ooi, K., Hong, J.Y., Monteiro Antunes, S., Alves, S., de Ulhoa Carvalho, M.L., Michalski, R.L.X.N., Kogan, P., Vida Manzano, J., García Quesada, R., Suárez Silva, E., Almagro Pastor, J.A., Nilsson, M.E., Axelsson, ., Gan, W.S., Watcharasupat, K.N., Jaratjarungkiat, S., Ong, Z.T., Dökmeci Yörükoğlu, P.N., Erçakmak Osma, U.B., Nguyen, T.L., 2024. Soundscape descriptors in eighteen languages: Translation and validation through listening experiments. Applied Acoustics 224, 110109. doi:10.1016/j.apacoust.2024.110109.