Pre-registered report: Space Sequence Synesthesia Diagnostic using form mapping

2025-10-29

Table of contents

1 Abstract:

Existent diagnostic tools for space sequence synethesia are based on questionnaire and response consistency. Consistency is calculated as the area between repetitions for the same inducer. In the first present phase, available data from 467 participants is used to explore new geometrical features to discriminate syntheses from controls. Conceptually, our goal is to take advantage of the inducer's ordinality that create synesthetic forms. For this aim, we harness a geography package to extract geometrical features to use as a test for synethesia. Reciever Operator Characteristics are used to select the features that best diagnose synesthesia. In a second phase to come, we test the predictive power of the new diagnostic features onto newly collected dataset.

2 Introduction

Humans with Sequence Space Synesthesia (SSS) represent ordered sequences in particular spatial positions. For example, August (i.e. the *inducer)* might be represented in the bottom left position (i.e. the position is here the *concurrent),* this position is relative to the concurrent position of the other months which could form a circle all together. In addition time units, numbers also take particular forms (**?**), not to be confused with the Mental Number Line [Dehaene to be found]. These forms are idiosyncratic, meaning they might vary across individuals. This makes it difficult to detect authentic SSS and therefore give precise estimates of prevalence in the population. Estimated prevalence for SSS in the general population spans between 4.4 % (**?**) and 14.2 % (**?**), see also (**?**; **?**). Hence a reliable diagnostic tool to detect SSS would also be useful to investigate SSS.

Diagnostic depends on the definition of the conditions under investigation. A strict definition of Synestheesia requires five different criteria (**?**). *Automaticity*: the *inducer* automatically triggers the *concurrent*. For example august might automatically trigger it's specific spatial location. *Unidirectionality*: while the *inducer* triggers the concurrent, the concurrent does not trigger the inducer. Hence the bottom left position doe not trigger August. *Consciousness*: The concurrent is consciously percieved. *Developmentally early*: the experience was already present during childhood. *Consistency*: the inducer-concurrent pair remains stable in time. For example, August triggers the same bottom left position. Consistency is arguably the most suited criteria to develop a diagnostic tool since it is relatively simple to implement in a behavioral task and quantify.

Hence given consistency, similar concurrent responses triggered by the same inducers can be used as a marker for authentic SSS. Consistency test have become golden standart for colour-grapheme synesthesia, where an inducer is presented (i.e. letters of the alphabet) and the participant is requested to selected the concurrent colour, using a colour picker. Individual consistency is then calculated as the distance between repeated colour responses to the same inducers. Interestingly, the best colour space to detect colour-grapheme synesthesia is CIE*LUV, a colour space developed to be isoform to human perception (**?**). Analogously to grapheme-colour synesthetes, consistency test can be used to diagnose SSS. In that tasks, it is repeatedly asked to report the position of the inducers on a screen. The total area between the responses of same inducer (i.e. a triangle if repeated three times) is then used as characteristic to diagnose SSS. The rationale being that consistent responses would lead to smaller area than inconsistent ones (**?**). This method resembles how number forms are describe in the single case study (**?**), see Experiment 1.

However characterizing synesthetes from non synesthetes using total area has several limitations. For example high consistency by non-synesthetes can be achieved by giving all responses on the same screen position (i.e. false positive). Moreover, this kond of criteria might bias the diagnosis to include synesthetes with straigth lines which leads to less variability than more complex forms(**?**).

The goal of the present registered report is to first identify new features characterizing synesthetes responses based on already available datasets and test the best working features on a future dataset. The new features are desgined to take advantage of two properties of synesthetic responses that have not been included in precedent consistency tests. First, sequentiality on top of single inducer responses the ordered position between subsequent induces is important. For example the relative position of August and the other months. From numerical cognition, ordinality has been aknowledged to be an important semantic property of numbers, also given their sequential acquisition (i.e. 1 is learned before 2). Second, thee particular synthetic forms of the sequential spatial location. These forms might have geometrical properties. For example months of the year might be represented circularly (as already described by (**?**) for numbers).

To take advantage of sequential and geometrical synesthetic forms, we harnessed a geo-spatial package(**?**) to extract geometrical features from participant x and y coordinate responses. This packages allows for example to build string or polygons for each repetition and compare different geometrical features. Those individual geometrical features are then compared using Receiver Operator Charactheristics (ROC) between individuals grouped as synesthes and control. In the present *phase I*,we compare ROC on three merged derivationdatasets using the same task on SSS Ward (**?**). In future *phase II*, we compare whether the features selected to diagnose SSS in *phase I,* on a validation dataset that is not yet acquired (registered report on the open science foundation: https://osf.io/9efjb/**).**

3 Methods

Phase I: present analyses. First, we reproduce the diagnostic criteria of each respective dataset. Second, we merge the dataset and compare the diagnostic criteria across datasets using Reciever Operator Charachteristics (ROC). Third, we compare wheter the featuers lead to somilar ROC charachteristics across the different sets (i.e. for months, weeks and numbers). Fourth, we compute new candidate geometrical features that could be used to diagnose SS. Finally we summarize and compare all ROC and select the best features that class synesthetes from control with the merged dataset.

Phase II: future analyses. On a future dataset using the same task, we will compare the predictive power of the selected features using ROC.

3.1 Materials

A the exception of (**?**) (see https://osf.io/6hq94/files/osfstorage), the data from (**?**; **?**) were collected online. The 29 inducers were: the 12 months of a year, 7 days of the week and 10 numbers (i.e. hindo-arabic numerals from 0 to 9). (**?**) Also presented 50 and 100 numerals, which we excluded here. (**?**) data is collected using the Syntoolkit.

3.2 Procedure

The details for each procedure is described in each respective article (**?**; **?**; **?**), here we describe the common task.

Each participant is presented with one one inducer at a time at the center of a otherwise white screen. The participant is instructed to click at the screen position that they visualize them. Inducers order is randomized and each inducer is repeated three times.

The order of the stimuli was randomised, but such that no stimulus was repeated until the previous batch of unique stimuli (N = 29) had been presented.

4 *Phase I* Methods

The data for *phase I,* comes from: (**?**),(**?**) (from: https://osf.io/p5xsd/files/osfstorage) and (**?**)

- Root (**?**)

```
[1] 0
```

```
Warning: Using one column matrices in `filter()` was deprecated in dplyr 1.1.0.
i Please use one dimensional logical vectors instead.
```

We exclude 91 participants for which we could not compute the *z-scores*.

4.1 *Phase I.* Population

dataSource	Ctl	Syn
PeterCor	21	12
Rothen	37	33
Ward	215	252

4.2 *Phase I.* Analysis

First, we replicate consistency methods found in the literature using the same task ((**?**; **?**; **?**; **?**)) and compare the results.

Second, we extract features based on the form. (C) We harness a geography package to compute segment based features (D) We compute polygon based features. (E) Convex Hull (F) Angles.

- Each feature is presented with the following structure:
  - Compute Feature
  - Example
  - Receiver Operator Characteristics (ROC)

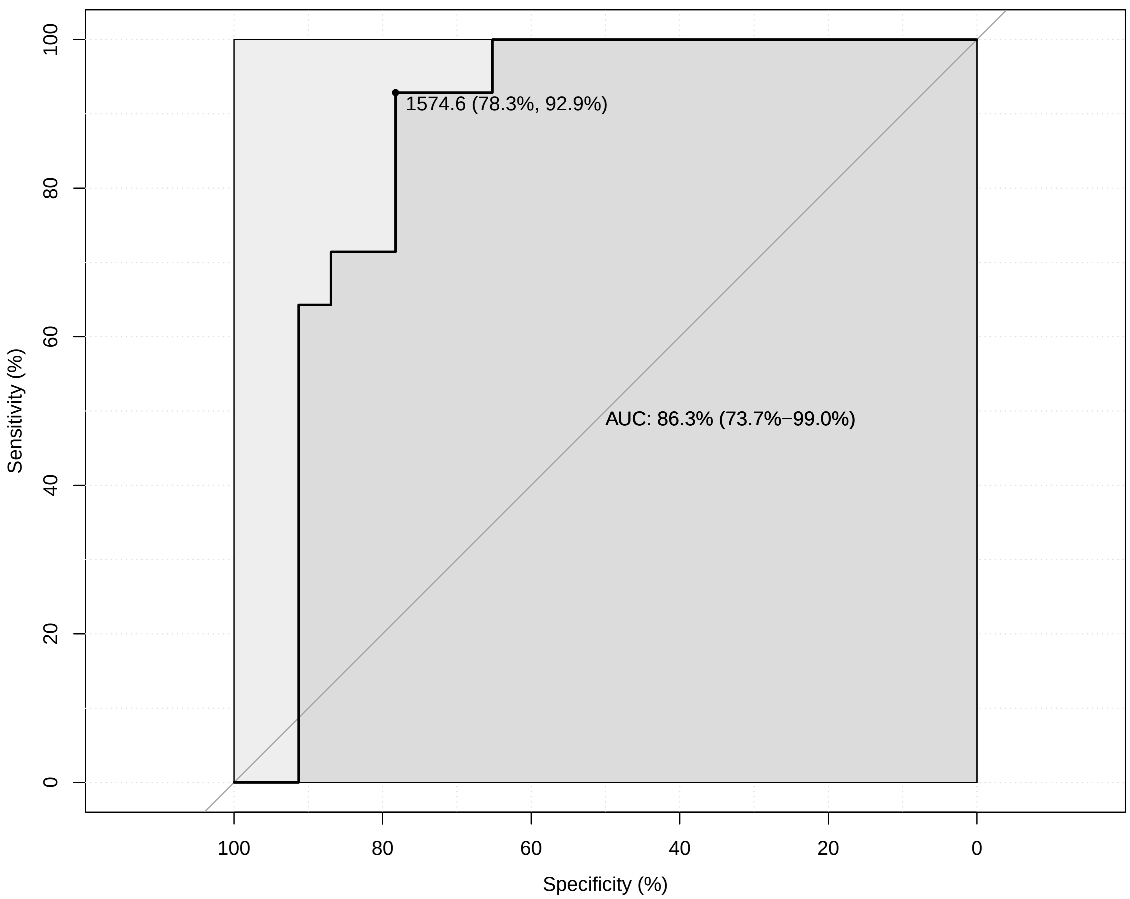
5 *Phase I.* Results Reproduce

5.1 Triangle area

Definition: Calculating consistency Each stimulus is represented by three xy coordinates - (x1, y1), (x2, y2), (x3, y3) - from the three repetitions. For each stimulus, the area of the triangle bounded by the coordinates is calculated as follows:
$Area = (x1y2 + x2y3 + x3y1 – x1y3 – x2y1 – x3y2)/2$

5.2 Reproduce Rothen et al., 2016.

Here we reproduce (**?**) ROC results:



Feature	AUC	threshold	sensitivity	specificity	ppv	npv	ci_low	ci_high
triangle_area_GA_Rothen	86.3354	1574.552	92.85714	78.26087	72.22222	94.73684	73.65815	99.01265

group	n	Mean	SD
Ctl	25	NaN	NA
Syn	15	NaN	NA

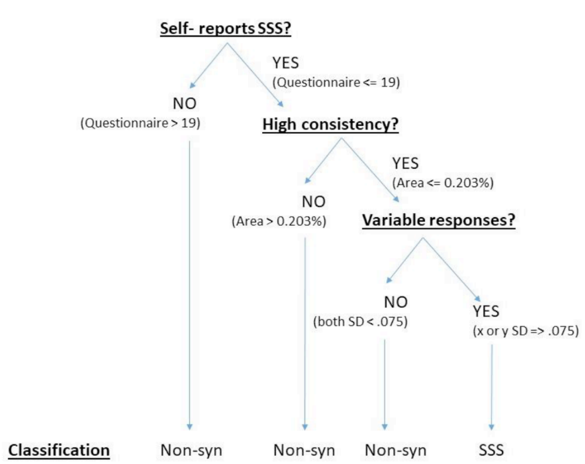
```
                  Feature     AUC threshold sensitivity specificity      ppv
1 triangle_area_GA_Rothen 86.3354  1574.552    92.85714    78.26087 72.22222
       npv   ci_low  ci_high
1 94.73684 73.65815 99.01265
```

5.2.1 Summary Rothen vs Reproduction

	Description	DP	AUC	Mean (syn)	Mean (con)	SD (syn)	SD (con)	Sensitivity	Specificity	Cut-off
Rothen	Area	1.57	0.76	1'079	7'031	1365	11'149	88	70	1'596
Repro			0.75	**1'312**	7'031	**1829**	11'303	**85**	70	1'575
Repro_Na			0.76	930	7'031	745	11'303	90	70	1'574

5.3 Reproduce Ward, 2020:

(**?**) combines different individual measures and features to diagnose synesthesia in comparison to randomly permuted z-score chance level thresholds:



Since we do not have questionnaire for all the data, we will only try to reproduce the consistency and sd combination.

The mean area is calculated by adding together the area for each stimulus and dividing by 29. This unit is transformed into a percentage area taking into account the different pixel resolution of each participant.Mean area $= SummedArea/ScreenArea$, where: $ScreenArea = Xpixels * Ypixels$

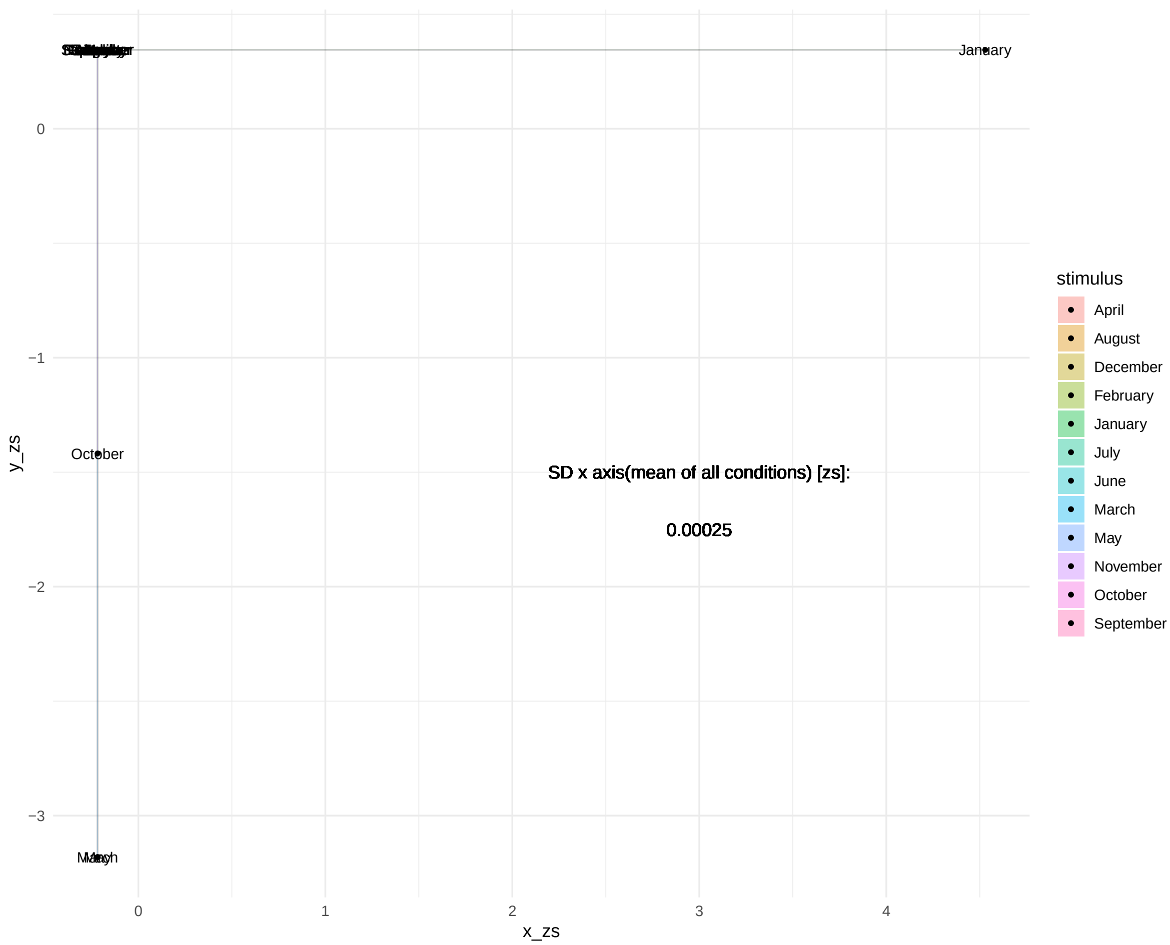
```
Adding missing grouping variables: `ID`
```

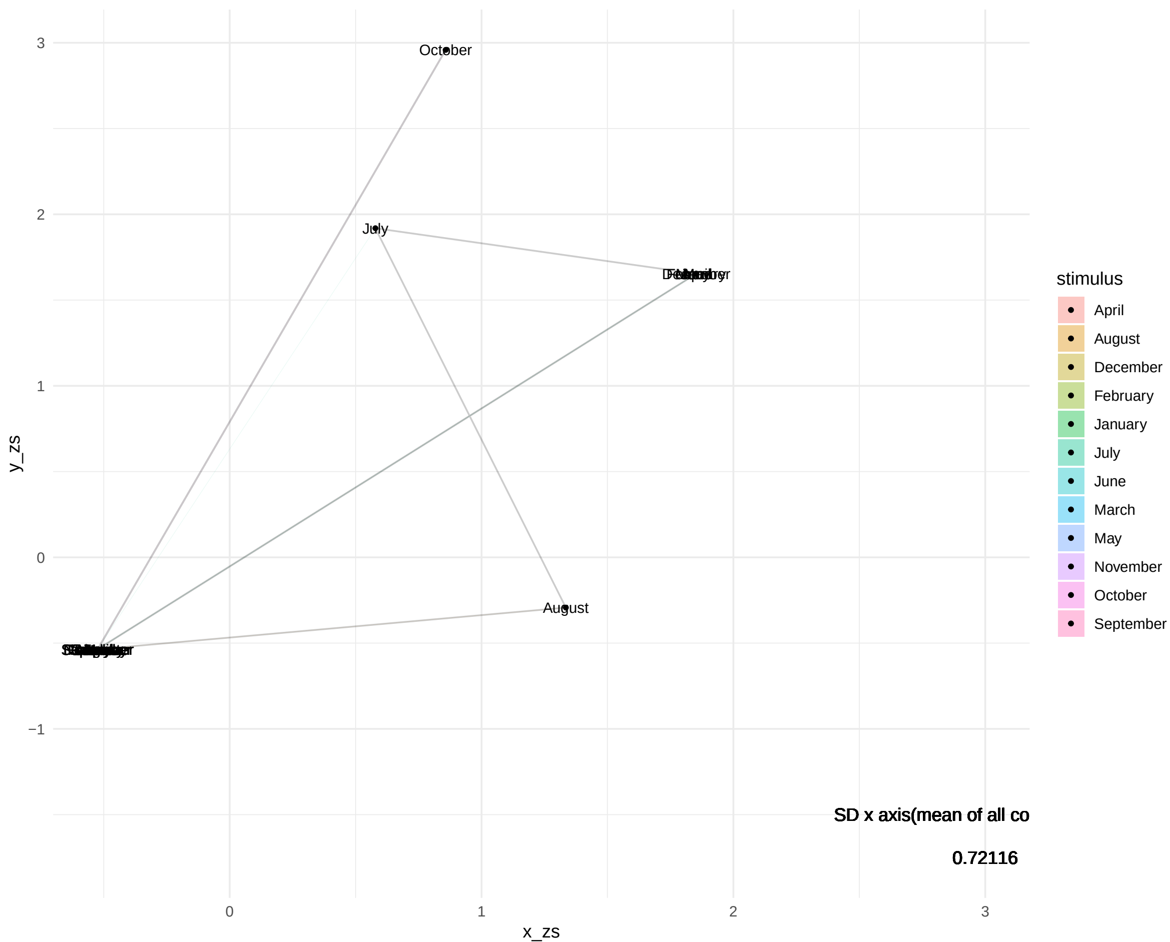
5.3.0.1 WIP here:

5.4 Add SD

5.4.1 Example

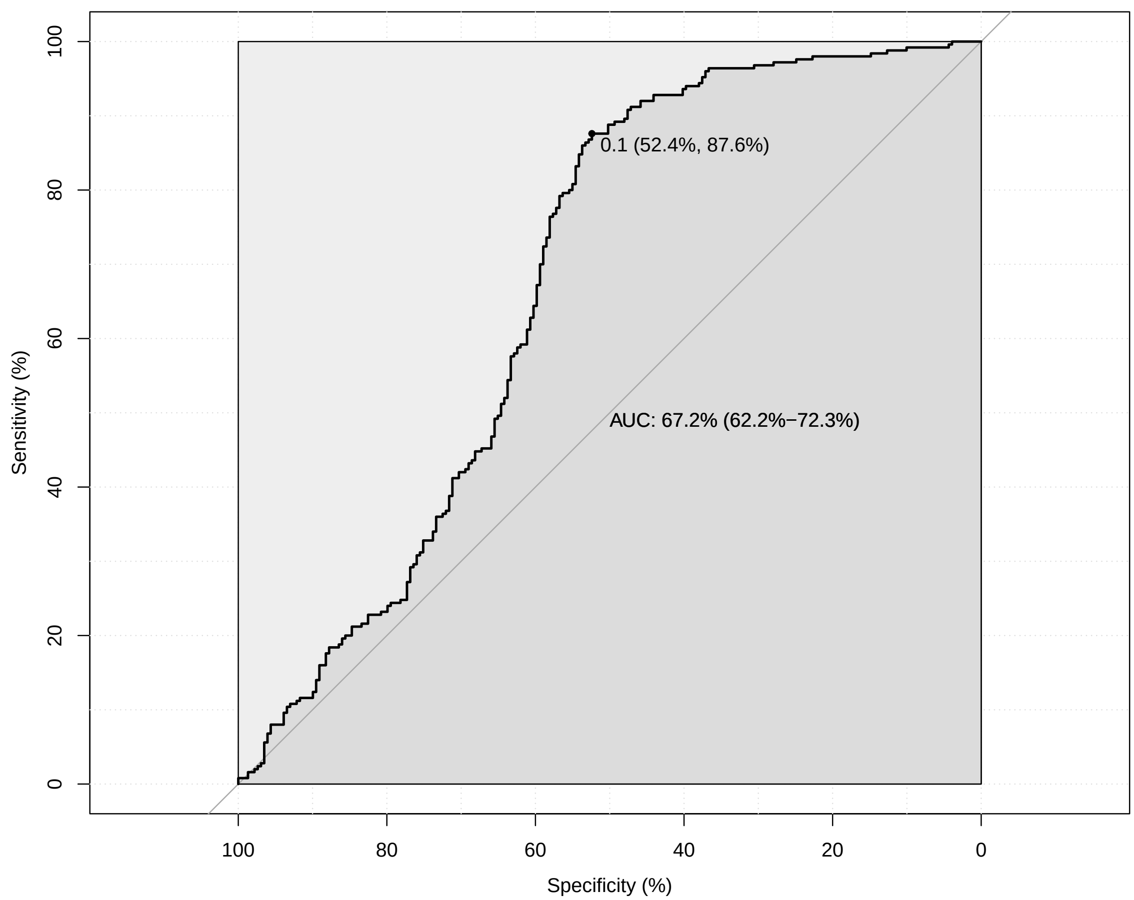
Would need an example with all in the center


January
October
SD x axis(mean of all conditions) [zs]:
0.00025
y_zs
x_zs
stimulus
April
August
December
February
January
July
June
March
May
November
October
September



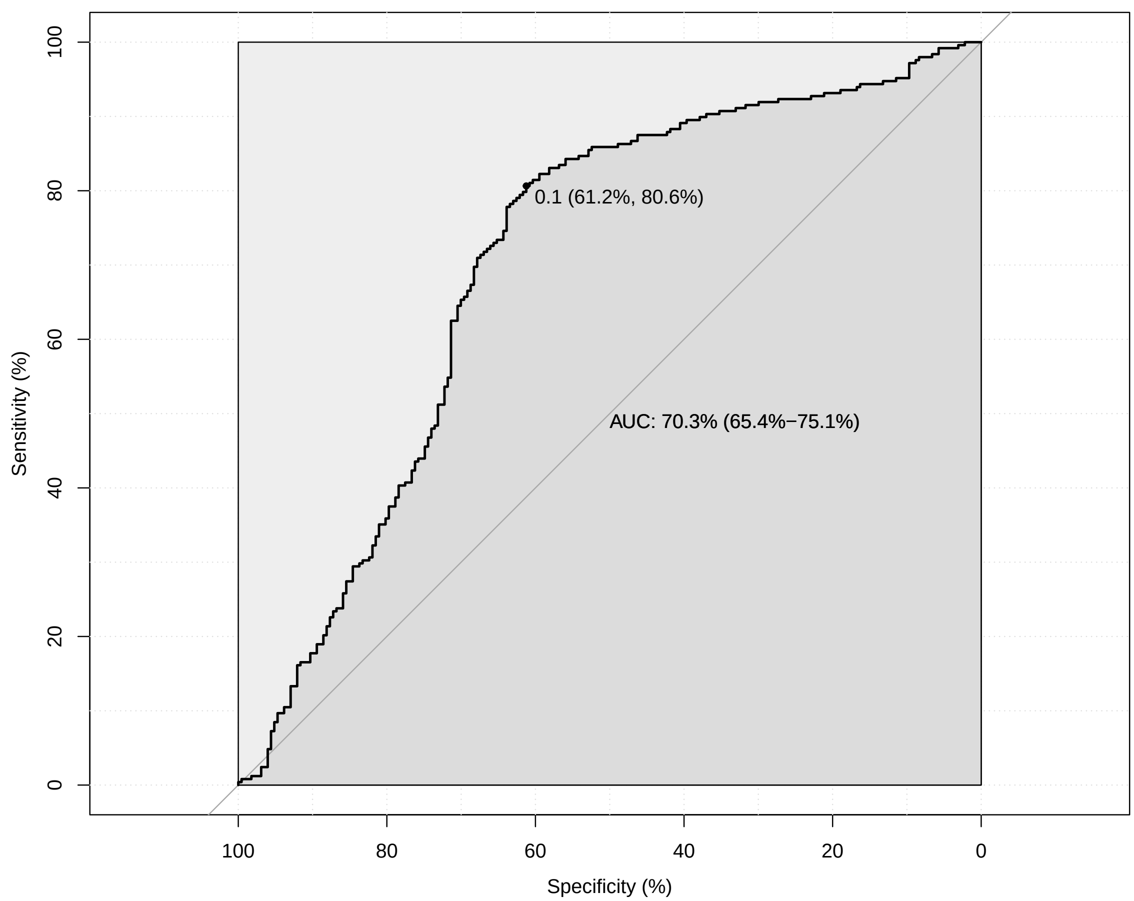
5.4.2 ROC

```
Setting levels: control = Ctl, case = Syn
```




```
$ROC_properties
    Feature     AUC threshold sensitivity specificity      ppv     npv   ci_low
1 SD_ID_xsc 67.2472 0.1217639        87.6    52.40175 66.76829 79.4702 62.20411
   ci_high
1 72.29021

$Coningency_table

      Ctl           Syn
  Ctl "120 (52.4%)" "109 (47.6%)"
  Syn "31 (12.4%)"  "219 (87.6%)"

$Descr_table
# A tibble: 2 x 4
  group     n  Mean     SD
```

```
  <fct> <int> <dbl>  <dbl>
1 Ctl     229 0.143 0.120
2 Syn     250 0.220 0.0854

Setting levels: control = Ctl, case = Syn

Setting levels: control = Ctl, case = Syn
```




```
$ROC_properties
    Feature     AUC threshold sensitivity specificity      ppv      npv  ci_low
1 SD_ID_ysc 70.2821 0.1179359    80.64516    61.23348 69.44444 74.33155 65.4266
   ci_high
1 75.13756
```

```
$Coningency_table

      Ctl           Syn
  Ctl "139 (61.2%)" "88 (38.8%)"
  Syn "48 (19.4%)"  "200 (80.6%)"

$Descr_table
# A tibble: 2 x 4
  group     n  Mean    SD
  <fct> <int> <dbl> <dbl>
1 Ctl     229    NA    NA
2 Syn     250    NA    NA

Setting levels: control = Ctl, case = Syn
```

5.5 Reproduce Root 2021

(**?**) suggested to use random permutations to calculate individual chance levels of consistency. Individual x and y coordinates (29 (inducers) *3 (repetitions) = 87) are randomly shuffled across conditions and inducers and areas are calculated for each 1000 permutations. Hence giving rise to individual distribution for chance level of consistency. Z-score is then computed to compare the observed with the permuted consistencies:

$Zscore = \frac{ObsConsistency - mean(PermConsistency)}{SD(PermConsistency)}$

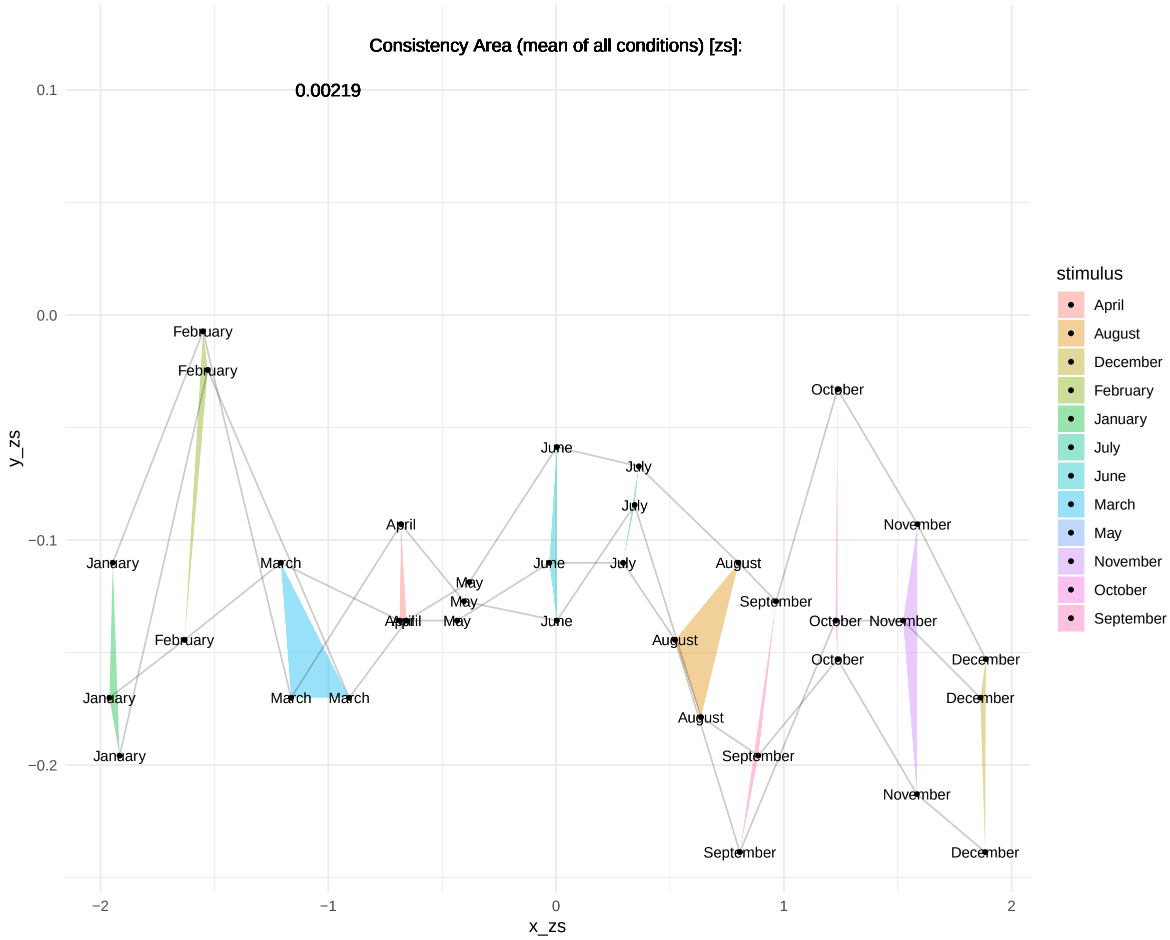
5.5.1 Example

5.5.2 ROC

5.6 Reproduced features on merged data:

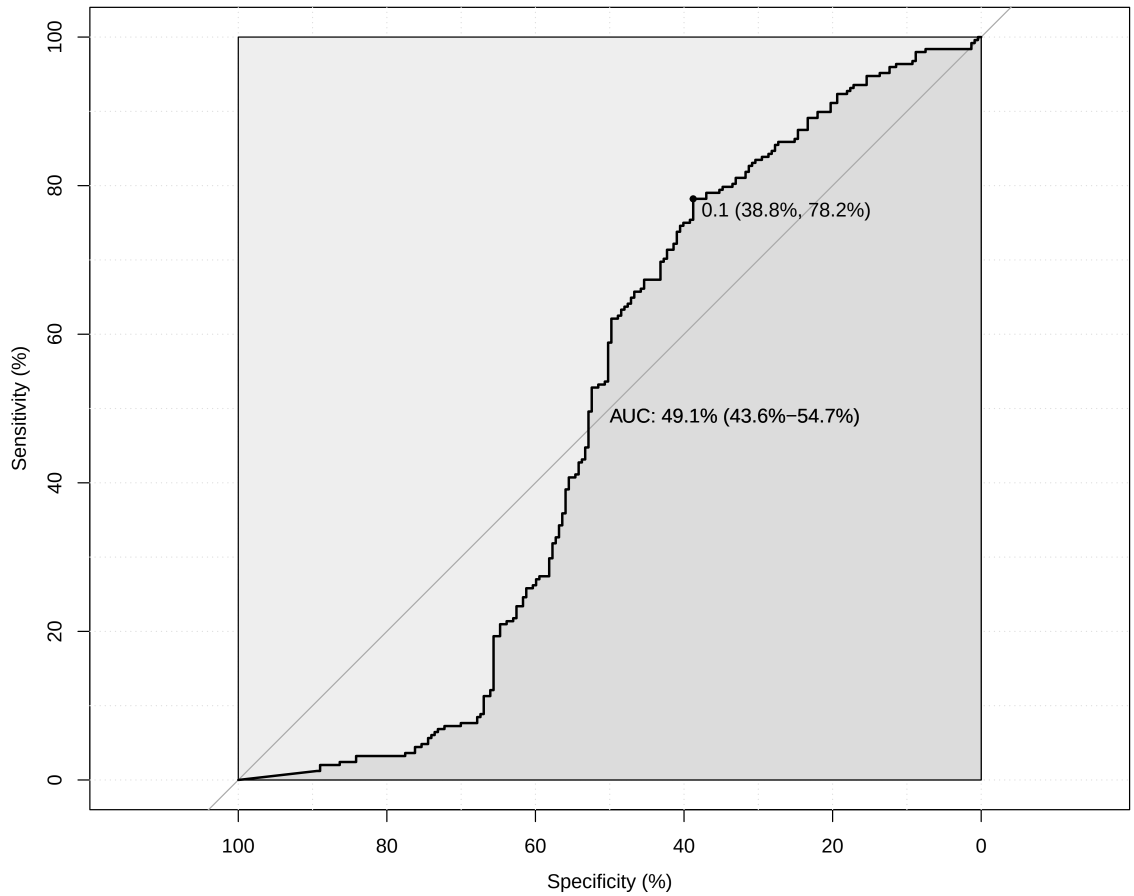
5.6.1 Area Consistency

5.6.1.1 Example



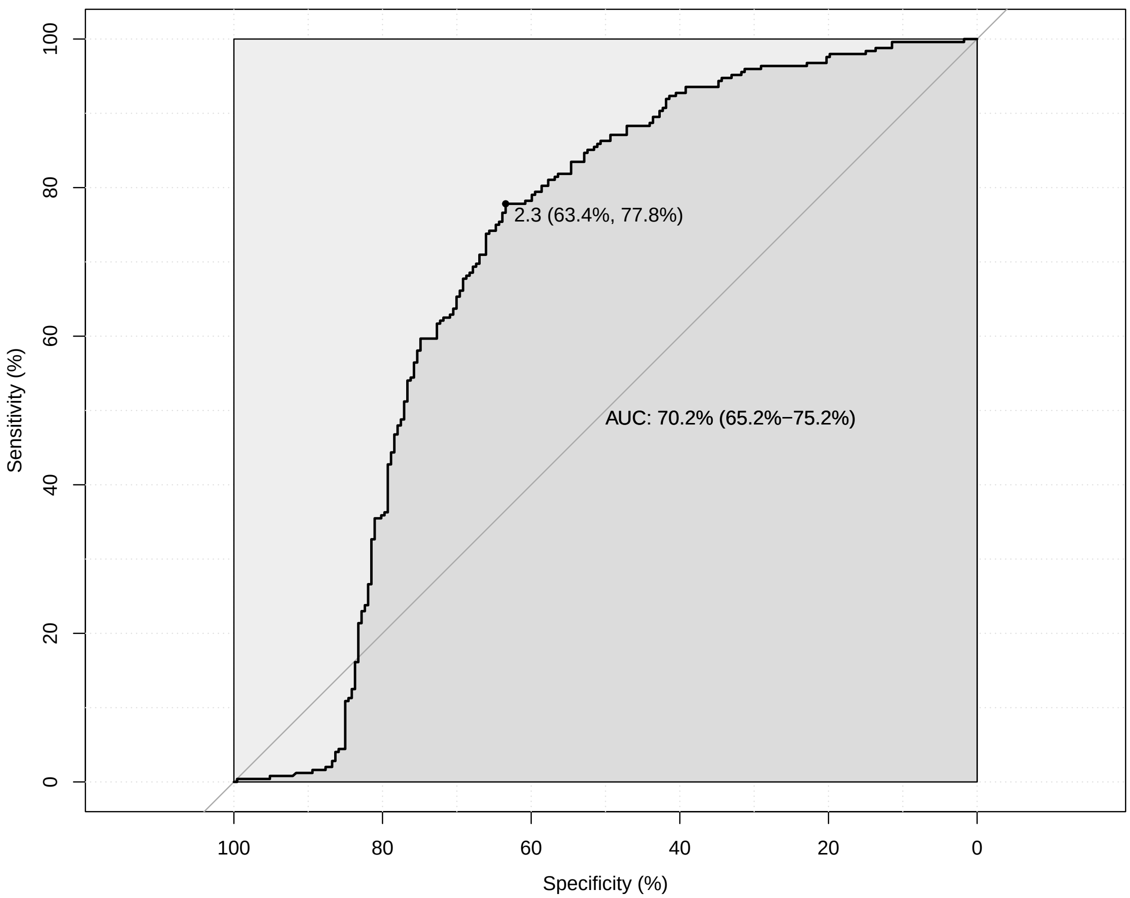
5.6.1.2 ROC

```
Setting levels: control = Ctl, case = Syn
```




```
$ROC_properties
      Feature     AUC  threshold sensitivity specificity      ppv      npv
1 Consistency 49.1385 0.05868314    78.22581    38.76652 58.25826 61.97183
    ci_low  ci_high
1 43.61052 54.66645

$Coningency_table

      Ctl          Syn
  Ctl "88 (38.8%)" "139 (61.2%)"
  Syn "54 (21.8%)" "194 (78.2%)"

$Descr_table
# A tibble: 2 x 4
  group     n  Mean    SD
```

```
  <fct> <int> <dbl> <dbl>
1 Ctl     229   NaN    NA
2 Syn     250   NaN    NA

Setting levels: control = Ctl, case = Syn
Setting levels: control = Ctl, case = Syn
```




```
$ROC_properties
         Feature     AUC threshold sensitivity specificity      ppv      npv
1 Consistency_zs 70.2137  2.272523    77.82258    63.43612 69.92754 72.36181
    ci_low  ci_high
1 65.18702 75.24037

$Coningency_table
```

```
      Ctl            Syn
  Ctl "144 (63.4%)" "83 (36.6%)"
  Syn "55 (22.2%)"  "193 (77.8%)"

$Descr_table
# A tibble: 2 x 4
  group     n  Mean    SD
  <fct> <int> <dbl> <dbl>
1 Ctl     229   NaN    NA
2 Syn     250   NaN    NA

Setting levels: control = Ctl, case = Syn
```

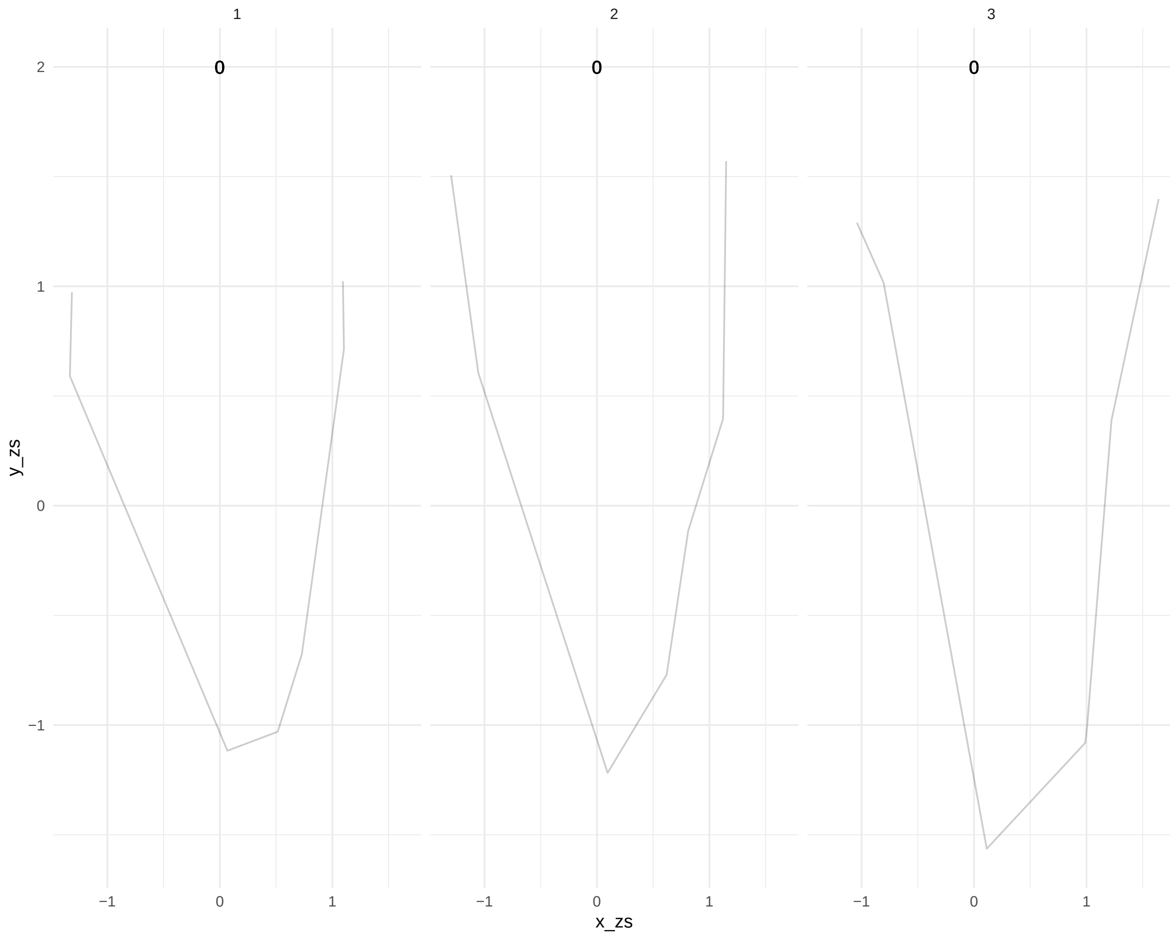
6 *Phase I.* Results: Novel features

6.1 Segment self-intersection

For each category we compute the number of times the path intersects within each repetition. This can be conceptualized as drawing a segment between the ordered inducers of each category (i.e. between 0 and 9 for numbers) and count how many line intersect. Hence the number of segment is `length(stimuli)-1`, for each participant we sum the number of self-intersections.

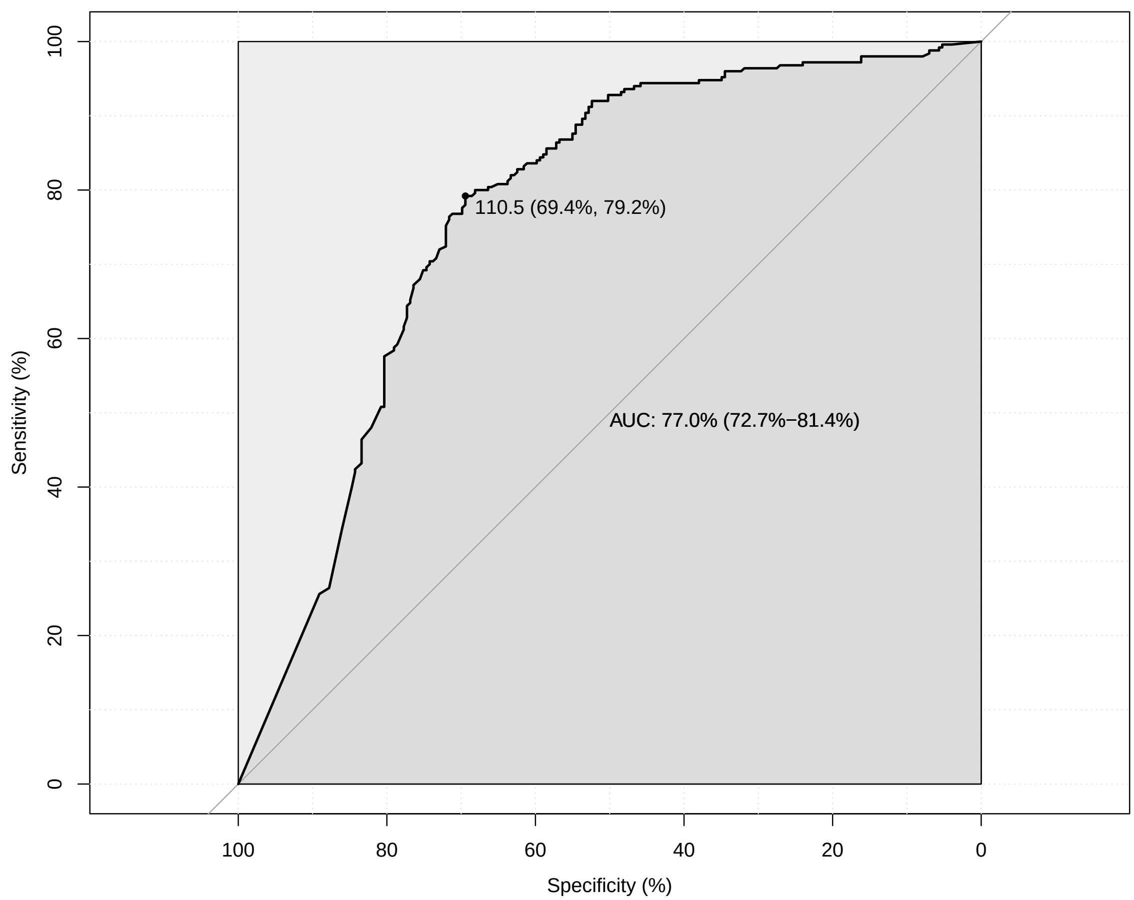
Note: ideally we should shuffle the repetitions.

6.1.1 Example



6.1.2 ROC

```
Setting levels: control = Ctl, case = Syn
```




```
$ROC_properties
          Feature     AUC threshold sensitivity specificity      ppv      npv
1 SumID_lineInter 77.0218     110.5        79.2    69.43231 73.8806 75.35545
    ci_low  ci_high
1 72.65798 81.38569

$Coningency_table

      Ctl           Syn
  Ctl "159 (69.4%)" "70 (30.6%)"
  Syn "52 (20.8%)"  "198 (79.2%)"

$Descr_table
# A tibble: 2 x 4
  group     n  Mean    SD
```

```
  <fct> <int> <dbl> <dbl>
1 Ctl     229 1099. 1079.
2 Syn     250  197.  538.
```

```
Setting levels: control = Ctl, case = Syn
```

7 Segments (with sf)

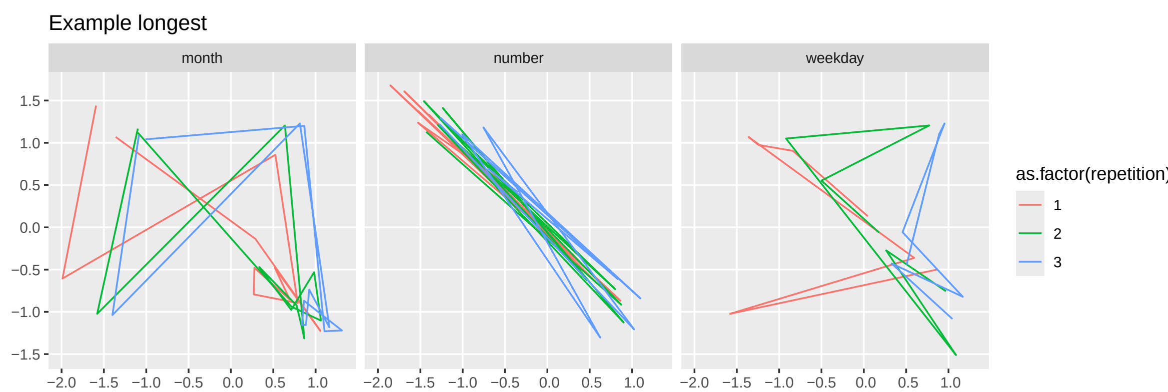
We will take advantage of the `sf` package and connect the x and y coordinates of ordered inducer with a segment. Sf hates NaN's. Either convert them to 0 (as originally) or remove them. I'll start converting to 0.

```
Linking to GEOS 3.13.0, GDAL 3.8.5, PROJ 9.5.1; sf_use_s2() is TRUE
```

```
Spherical geometry (s2) switched off
```

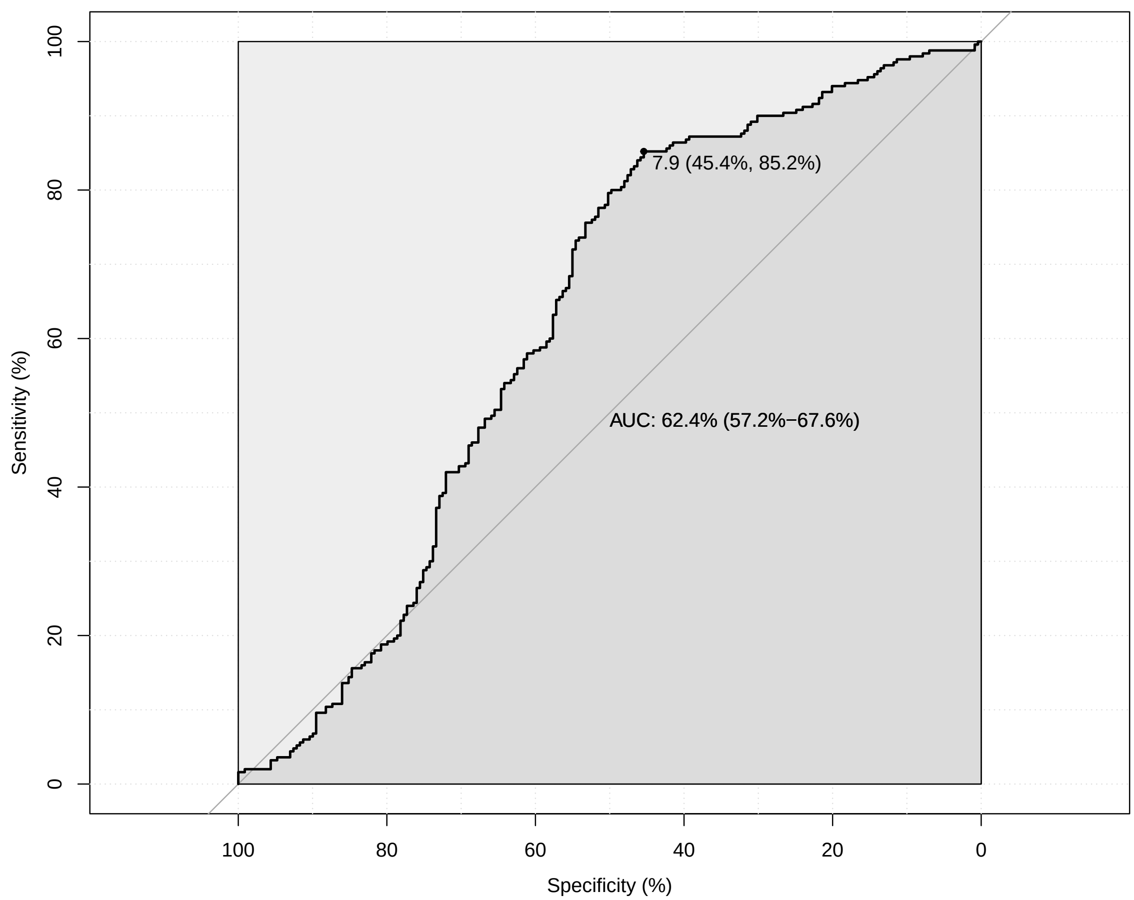
8 Segment length (should replicate Rothen)

8.1 Example



8.2 ROC

```
Setting levels: control = Ctl, case = Syn
```




```
$ROC_properties
       Feature     AUC threshold sensitivity specificity      ppv      npv
1 GA_segm_leng 62.3913  7.858334        85.2    45.41485 63.01775 73.75887
    ci_low  ci_high
1 57.22086 67.56168

$Coningency_table

      Ctl           Syn
  Ctl "104 (45.4%)" "125 (54.6%)"
  Syn "37 (14.8%)"  "213 (85.2%)"

$Descr_table
# A tibble: 2 x 4
  group     n  Mean    SD
```

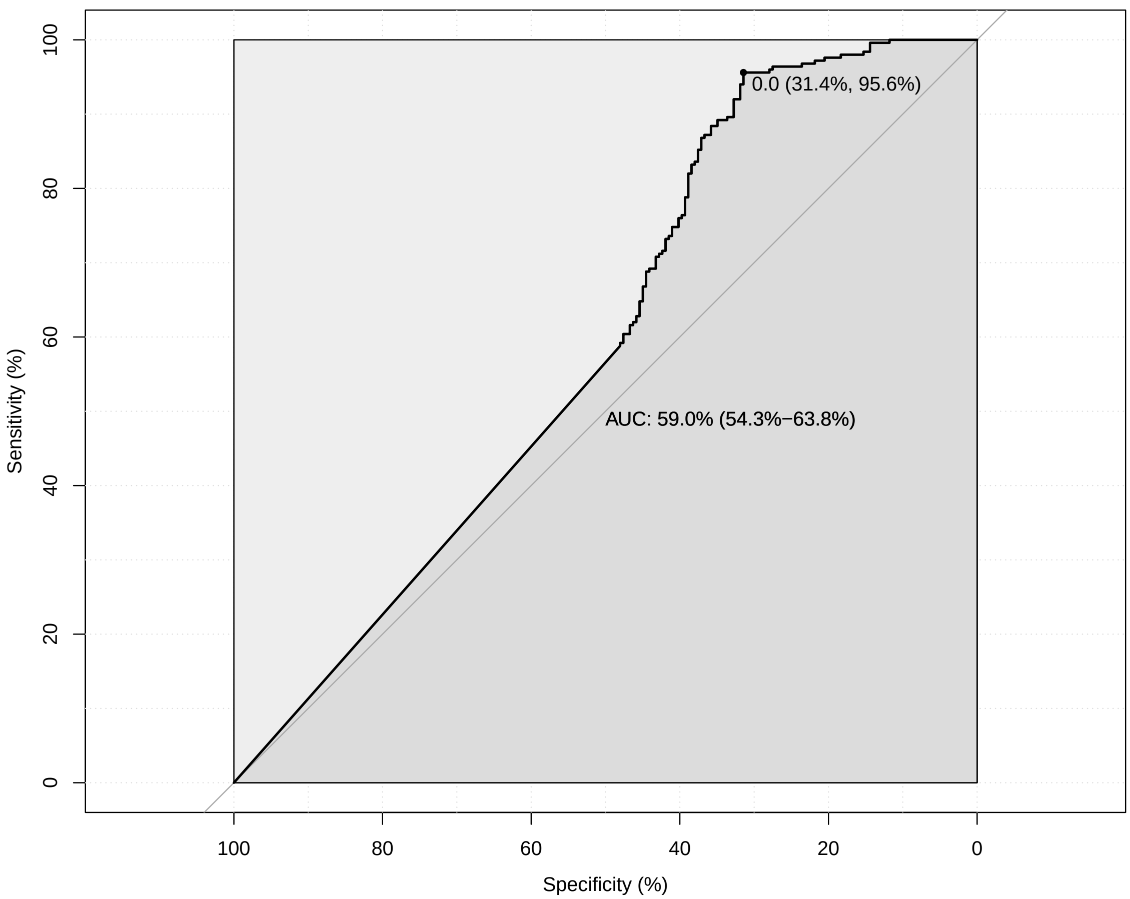
```
  <fct> <int> <dbl> <dbl>
1 Ctl     229  7.39  3.02
2 Syn     250  6.14  2.19

Setting levels: control = Ctl, case = Syn
```

9 Distances between repetitions

9.1 Example

9.2 ROC

```
Setting levels: control = Ctl, case = Syn
```

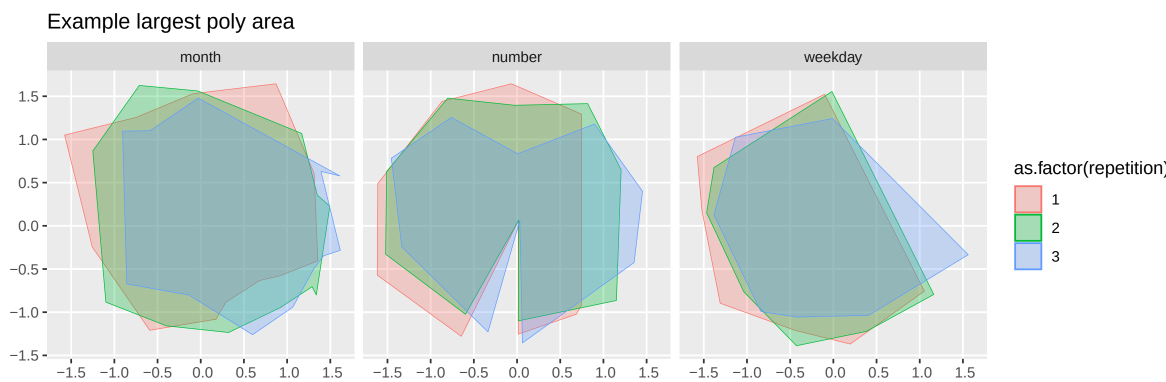


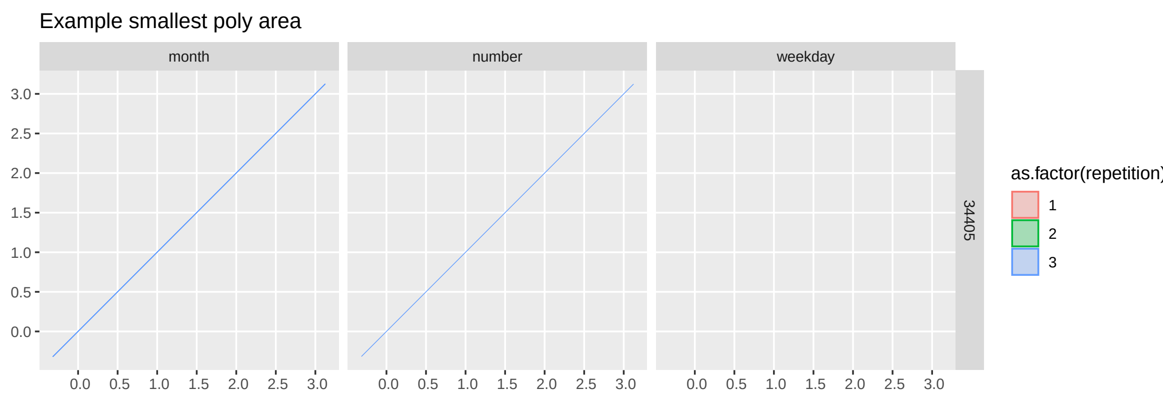
```
$ROC_properties
     Feature     AUC  threshold sensitivity specificity      ppv      npv
1 GA_BtwDist 59.0279 0.03093695        95.6    31.44105 60.35354 86.74699
    ci_low  ci_high
1 54.28596 63.76993

$Coningency_table

      Ctl          Syn
  Ctl "72 (31.4%)" "157 (68.6%)"
  Syn "11 (4.4%)"  "239 (95.6%)"

$Descr_table
# A tibble: 2 x 4
  group     n   Mean     SD
  <fct> <int>  <dbl>  <dbl>
1 Ctl     229 0.0932 0.184
2 Syn     250 0.0103 0.0445

Setting levels: control = Ctl, case = Syn
```

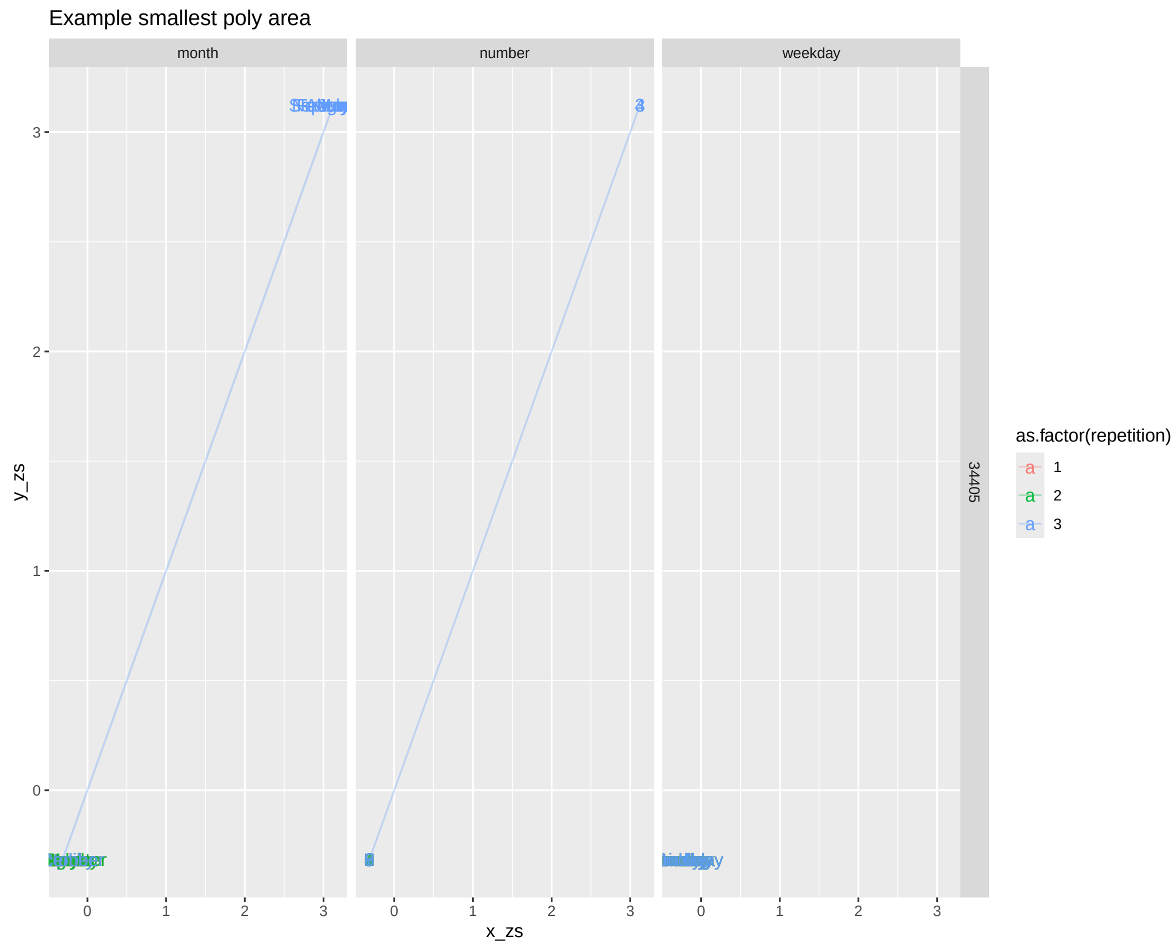
10 Polygon based geometries

11 Polygon area

11.1 Example

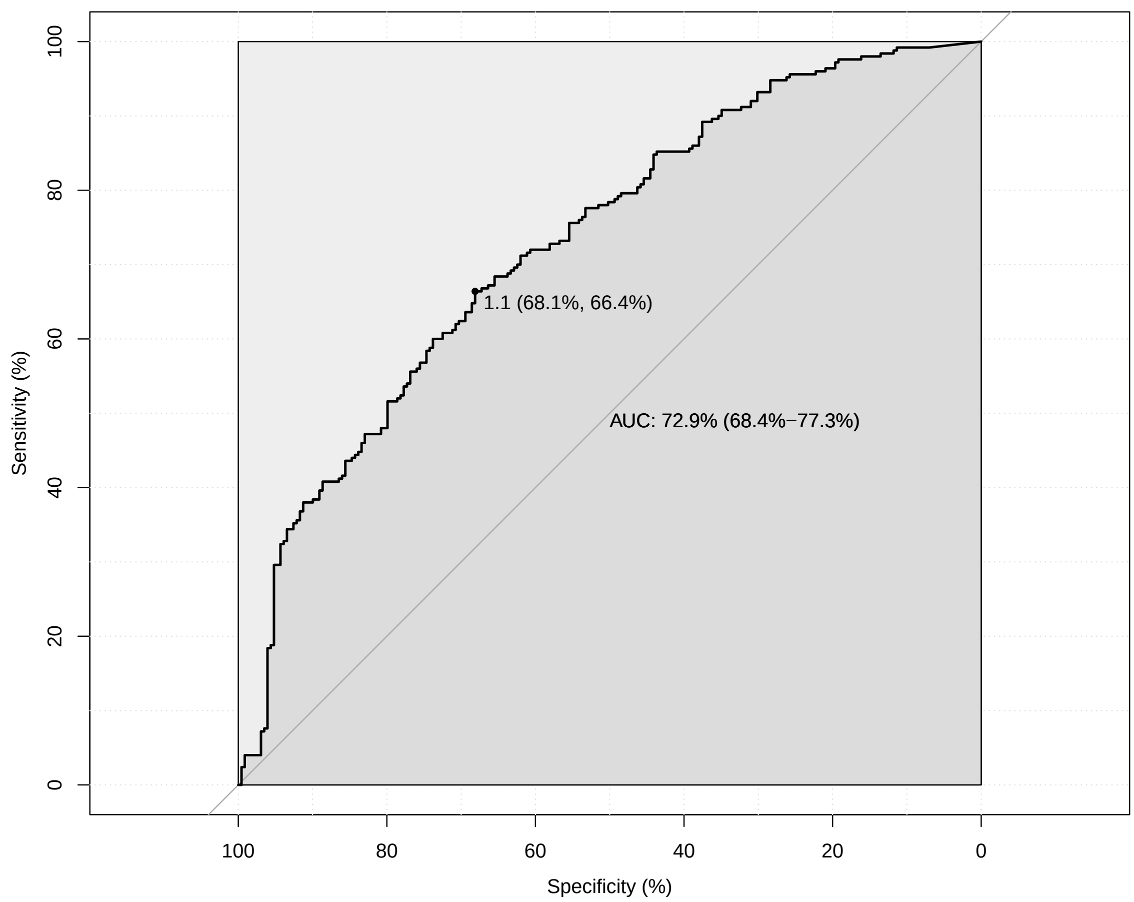



Example smallest poly area
month
number
weekday
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
34405
as.factor(repetition)
1
2
3



11.2 ROC

```
Setting levels: control = Ctl, case = Syn
```

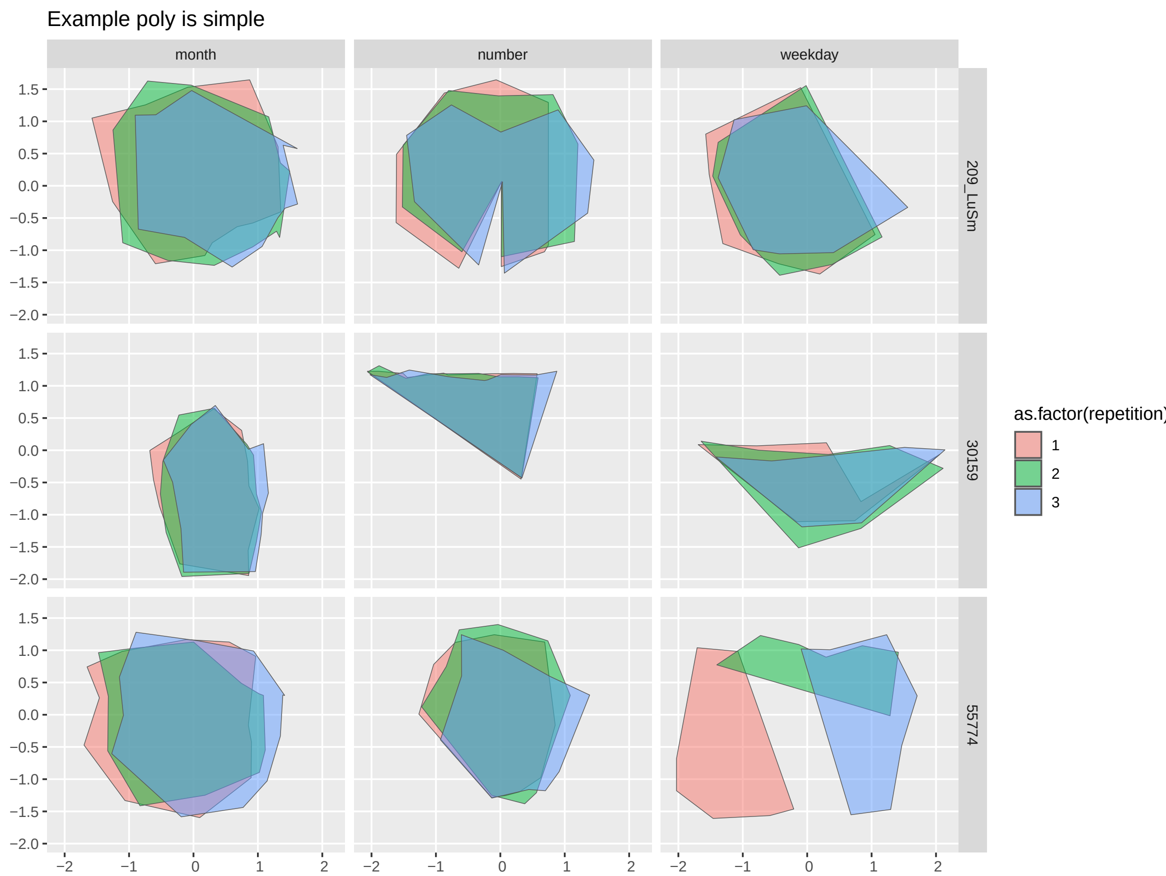


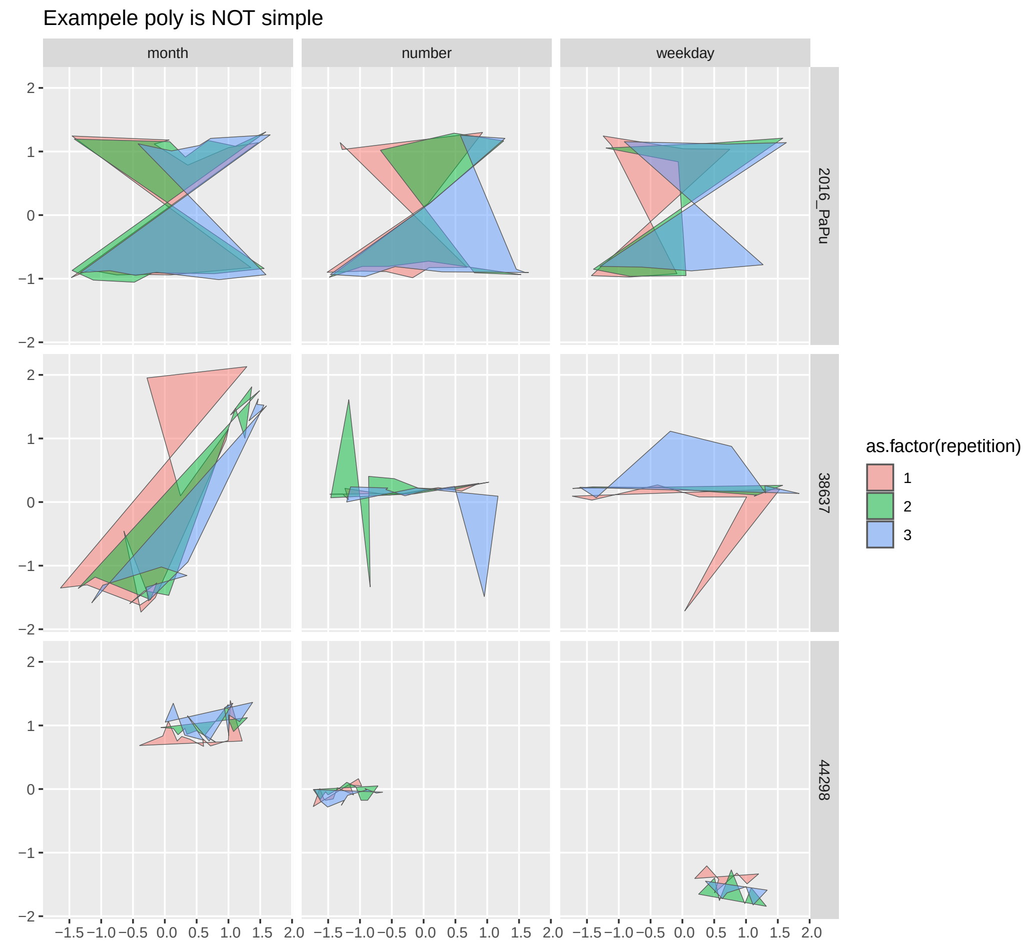

```
$ROC_properties
      Feature     AUC threshold sensitivity specificity      ppv npv   ci_low
1 GA_areaPoly 72.8769  1.105635        66.4    68.12227 69.45607  65 68.40784
   ci_high
1 77.34587

$Coningency_table

      Ctl            Syn
  Ctl "156 (68.1%)" "73 (31.9%)"
  Syn "84 (33.6%)"  "166 (66.4%)"

$Descr_table
# A tibble: 2 x 4
  group     n  Mean    SD
```

```
  <fct> <int> <dbl> <dbl>
1 Ctl     229 0.895  1.01
2 Syn     250 1.81   1.30

Setting levels: control = Ctl, case = Syn
```

12 Polygon simplicity

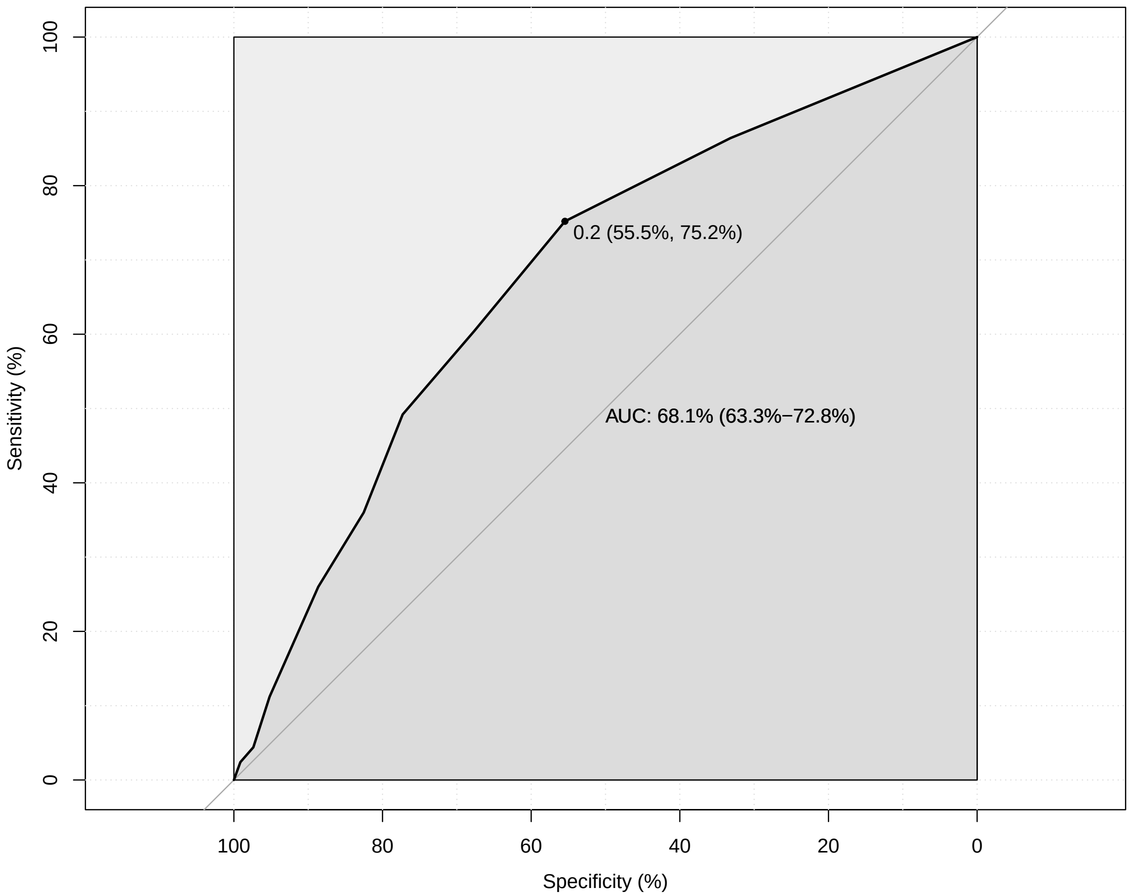
12.1 Example





12.2 ROC

```
Setting levels: control = Ctl, case = Syn
```




```
$ROC_properties
      Feature     AUC threshold sensitivity specificity      ppv      npv
1 GA_isSimple 68.0664 0.1666667        75.2    55.45852 64.82759 67.19577
    ci_low  ci_high
1 63.31827 72.81448

$Coningency_table

      Ctl           Syn
  Ctl "127 (55.5%)" "102 (44.5%)"
  Syn "62 (24.8%)"  "188 (75.2%)"

$Descr_table
# A tibble: 2 x 4
  group     n  Mean    SD
```

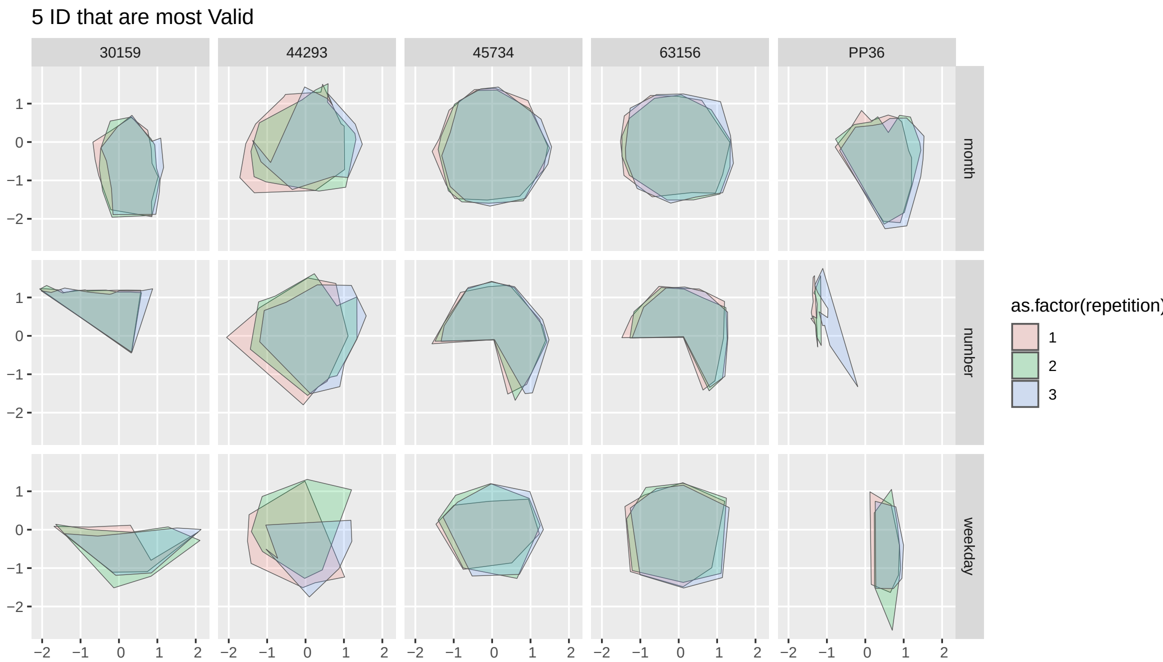
```
  <fct> <int> <dbl> <dbl>
1 Ctl     229 0.226 0.250
2 Syn     250 0.390 0.270

Setting levels: control = Ctl, case = Syn
```

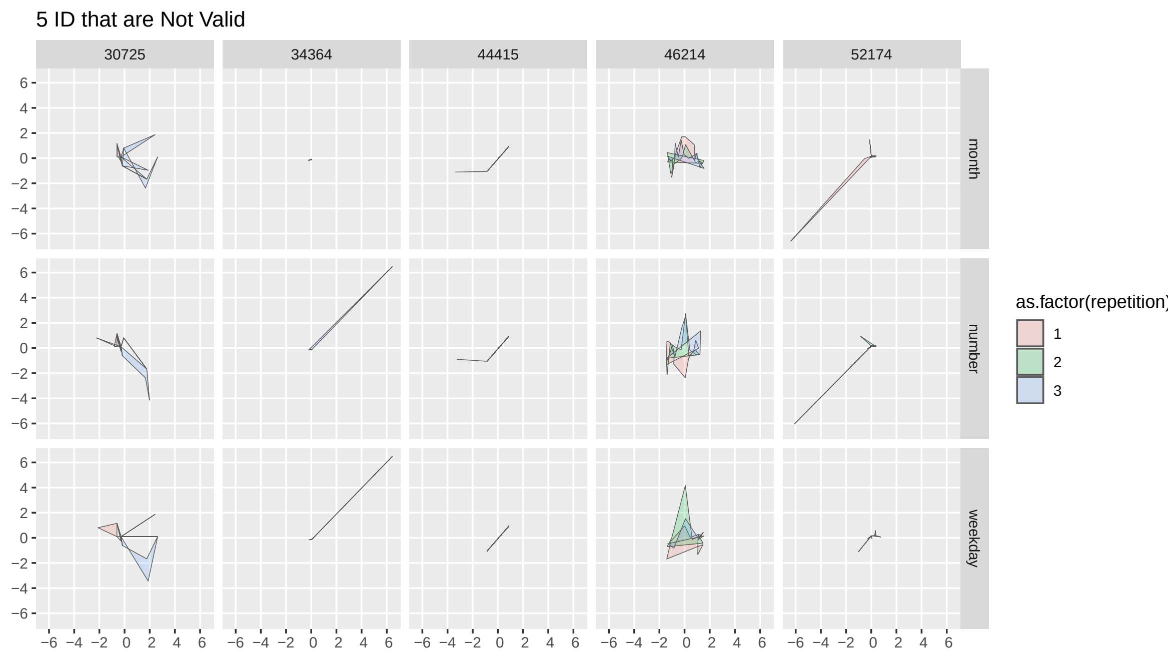
13 Topological validity Structure

is topologically valid:

From the package description: *"For projected geometries, st_make_valid uses the lwgeom_makevalid method also used by the PostGIS command ST_makevalid if the GEOS version linked to is smaller than 3.8.0, and otherwise the version shipped in GEOS; for geometries having ellipsoidal coordinates s2::s2_rebuild is being used."* From https://postgis.net/docs/ST_IsValid.html: *value is well-formed and valid in 2D according to the OGC rules.* (Open Geopsatial Consotrtium)

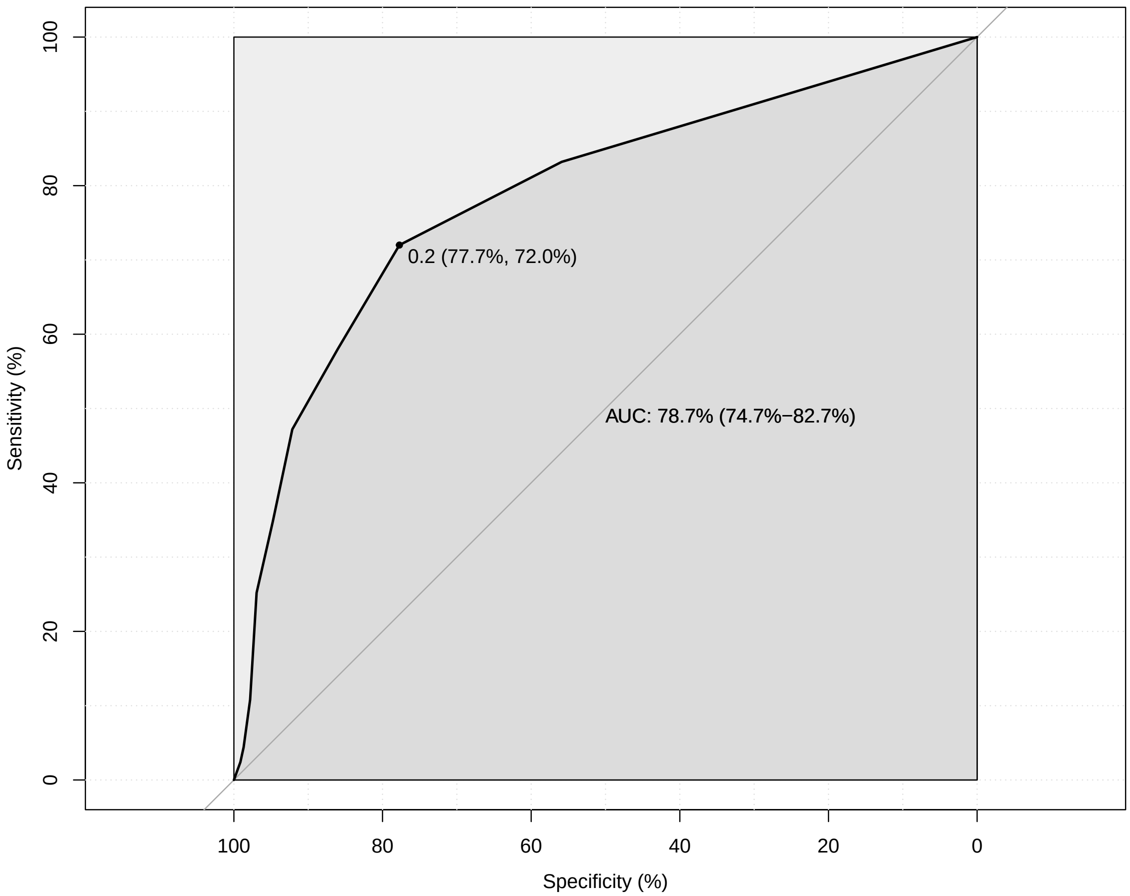
13.1 Example


5 ID that are most Valid
30159
44293
45734
63156
PP36
month
number
weekday
as.factor(repetition)
1
2
3
−2
−1
0
1
2



13.2 ROC

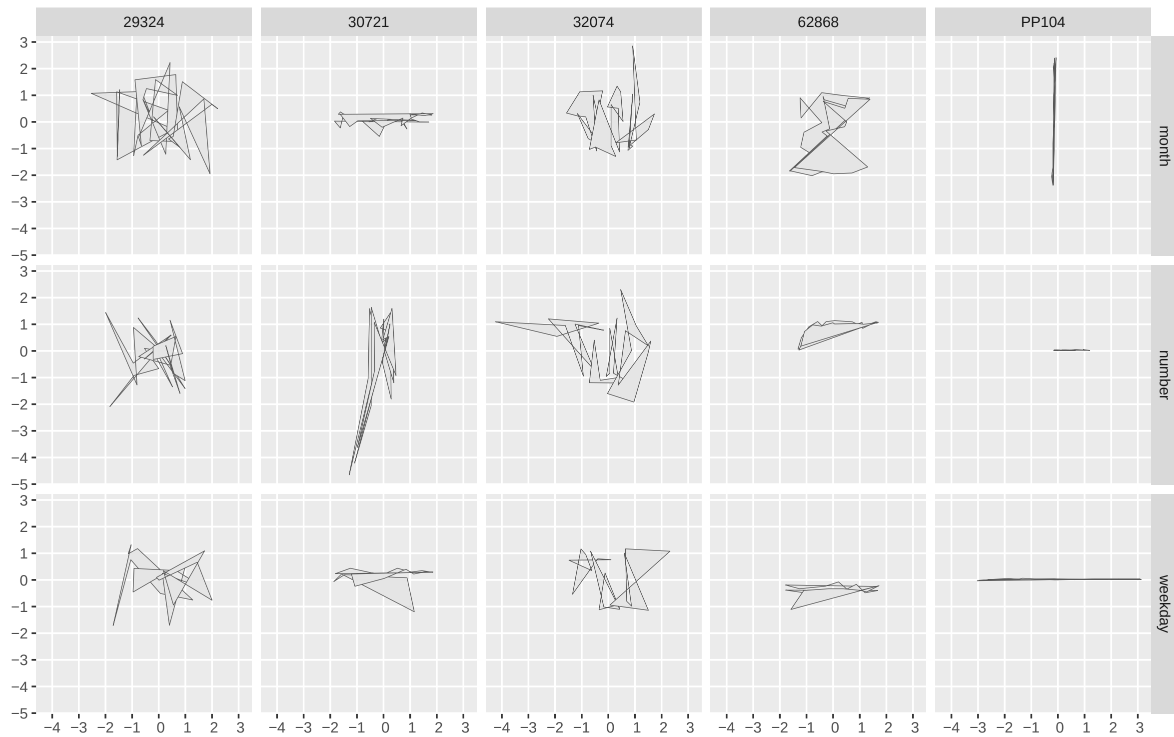
```
Setting levels: control = Ctl, case = Syn
```

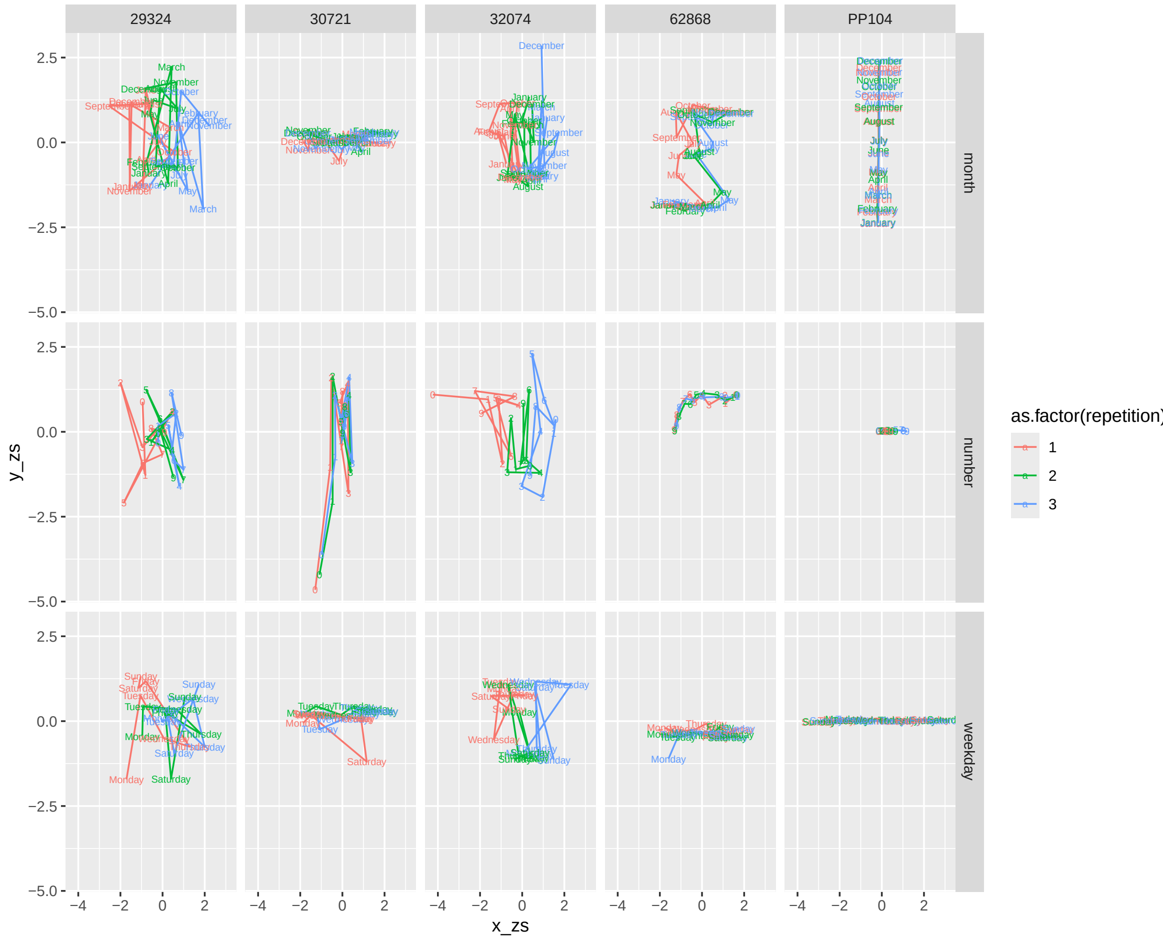


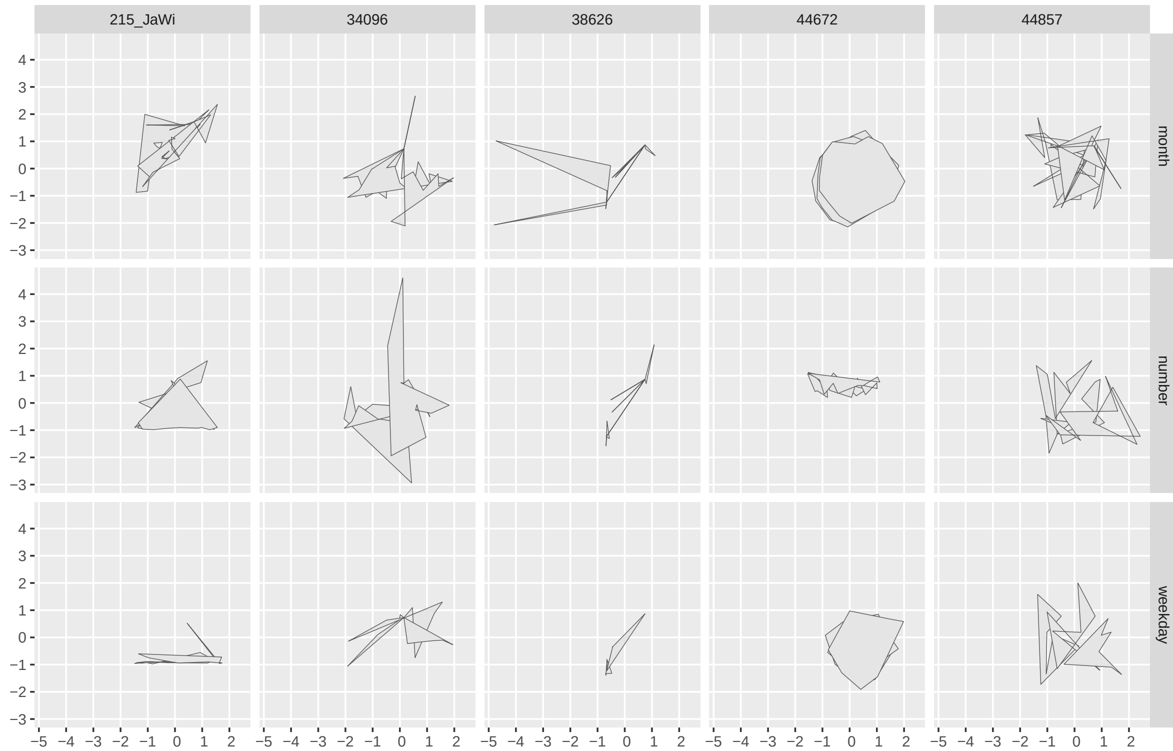

```
$ROC_properties
           Feature     AUC threshold sensitivity specificity      ppv      npv
1 GA_isValidStruct 78.7301 0.1666667          72    77.72926 77.92208 71.77419
    ci_low  ci_high
1 74.72564 82.73462

$Coningency_table

      Ctl            Syn
  Ctl "178 (77.7%)" "51 (22.3%)"
  Syn "70 (28%)"    "180 (72%)"

$Descr_table
# A tibble: 2 x 4
  group     n  Mean    SD
```

```
  <fct> <int> <dbl> <dbl>
1 Ctl     229 0.112 0.186
2 Syn     250 0.376 0.276

Setting levels: control = Ctl, case = Syn
```

13.2.1 Extra: Visualize false pos and neg




29324
30721
32074
62868
PP104
month
number
weekday
y_zs
x_zs
as.factor(repetition)
1
2
3
2.5
0.0
−2.5
−5.0
−4
−2
0
2


215_JaWi
34096
38626
44672
44857
month
number
weekday
−5 −4 −3 −2 −1 0 1 2
−3 −2 −1 0 1 2 3 4