

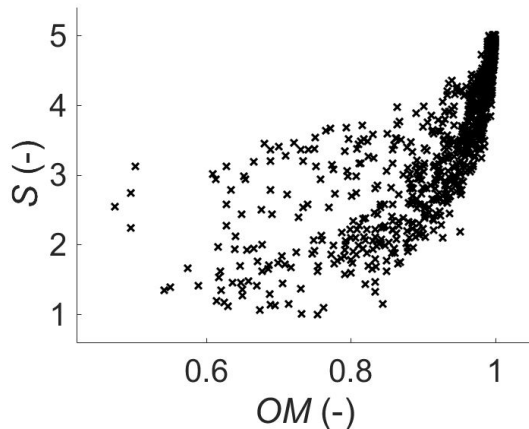
# Methodology for Objective Metrics Performance Evaluation...

## ... and its use for large scale training

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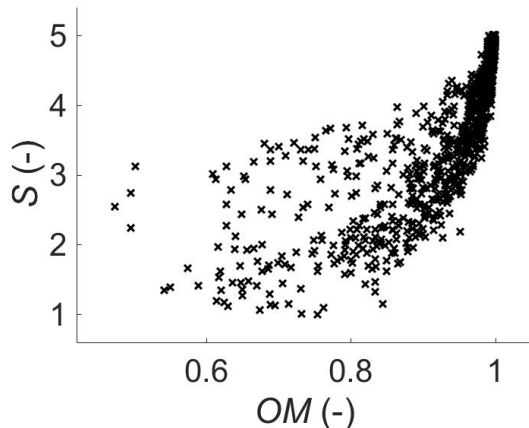
# Objective Metrics Performance Evaluation

- Comparing subjective vs. automatically predicted scores ( $S$  vs.  $OM$ )



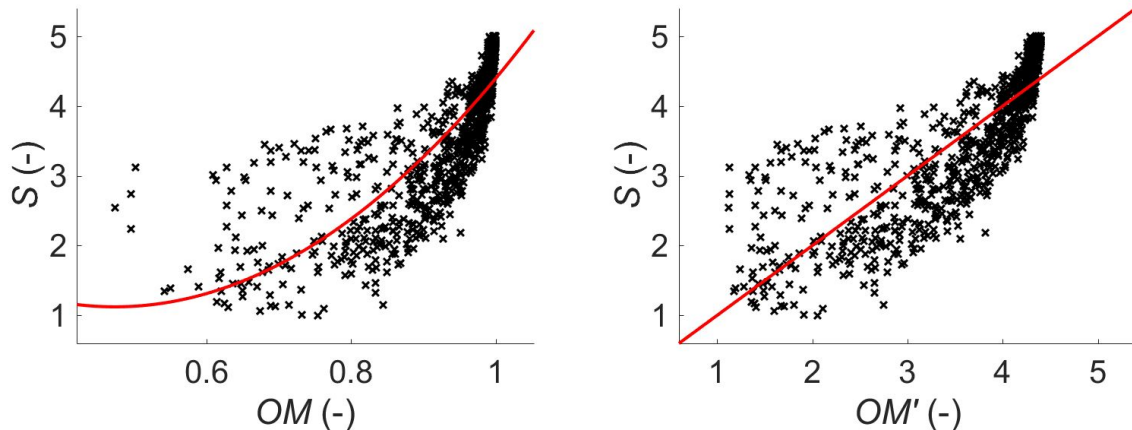
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- Typical measures [ITU-T Rec. P.1401]
  - Pearson Correlation Coefficient
  - Root Mean Squared Error
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- ➡ **Necessity of mapping to the common scale**



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  - Mapping can bias the results

Correlation for CSIQ database after 3rd order polynomial mapping	SSIM	MS-SSIM
Fitting function coefficients optimized with PLCC (VQEG)	<b>0.8575</b>	0.8562
Fitting function coefficients optimized with RMSE (ITU-T Rec. J.149)	0.8581	<b>0.8859</b>

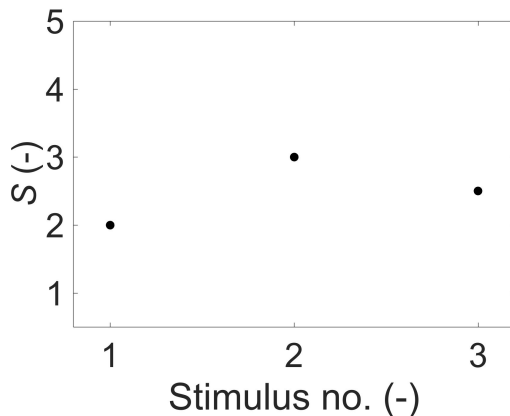
# Rank Order Correlation

- Using Rank Order Correlation Coefficients (Spearman's and/or Kendall's)
  - Typical solution to the mapping problem - independency towards the monotonic mapping



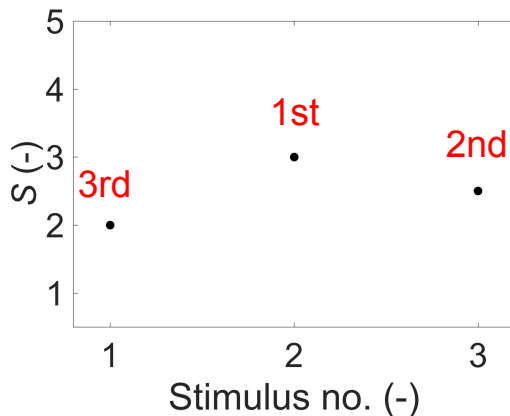
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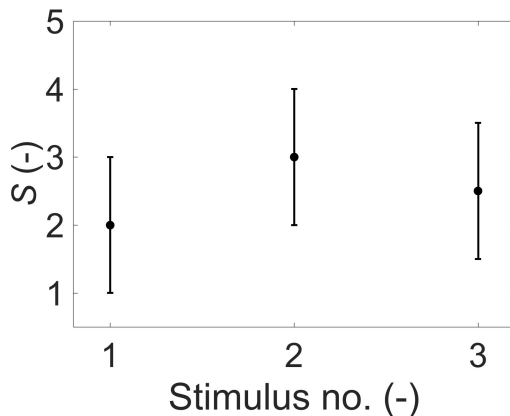
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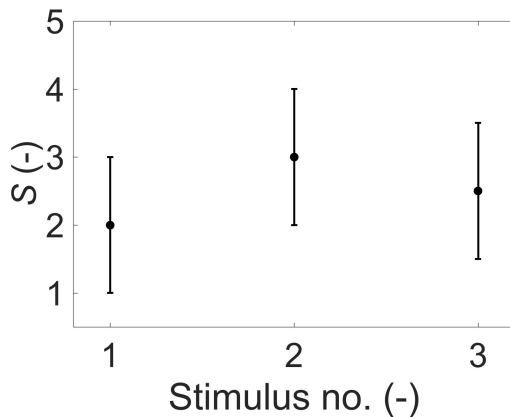
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What is the correct order?

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**(a) *Are any two stimuli statistically significantly different in quality?***

$$[i,j] \in \text{N} \Leftrightarrow \Pr\{ S(i) \neq S(j) \} < 1-\alpha$$

$$[i,j] \in \text{D} \Leftrightarrow \Pr\{ S(i) \neq S(j) \} \geq 1-\alpha$$

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**(b) *If they are, which of them is qualitatively better?***

$$\begin{aligned} [i,j] \in \text{B} &\Leftrightarrow \Delta S(i,j) = S(i) - S(j) \geq 0, \forall [i,j] \in \text{D} \\ [i,j] \in \text{W} &\Leftrightarrow \Delta S(i,j) = S(i) - S(j) \leq 0, \forall [i,j] \in \text{D} \end{aligned}$$



# Novel performance evaluation methodology: Proposed Assumptions

- Reliable metric then

I. Provides **close** scores for **similar** pairs and **distant** scores for **different**

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- II. Provides **higher** score for qualitatively **better** stimulus

$$\text{sign} \{ \Delta OM(i,j) \} = \text{sign} \{ \Delta S(i,j) \}, \forall [i,j] \in \mathbf{D}$$

# Novel performance evaluation methodology:

## Description

*S, CI, OM*

Dataset(s)

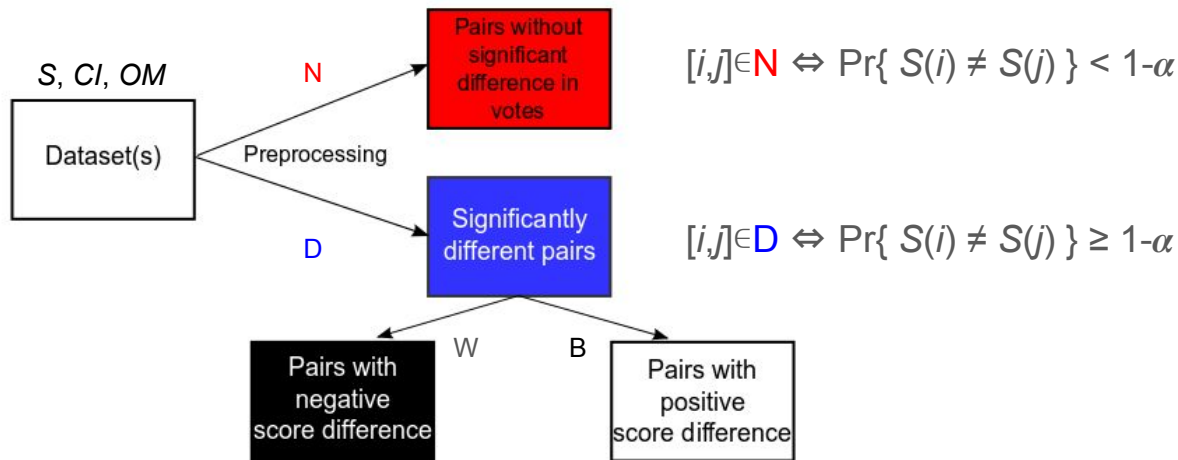
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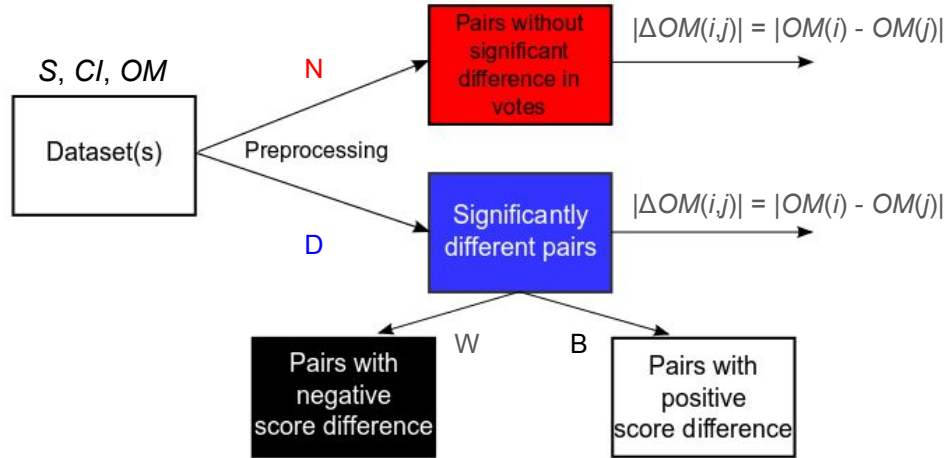


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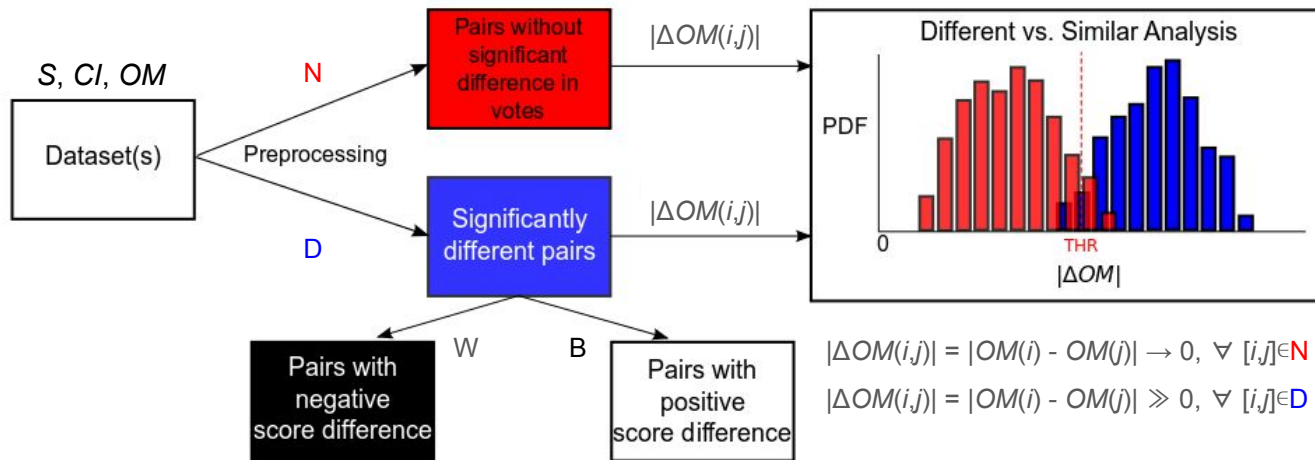
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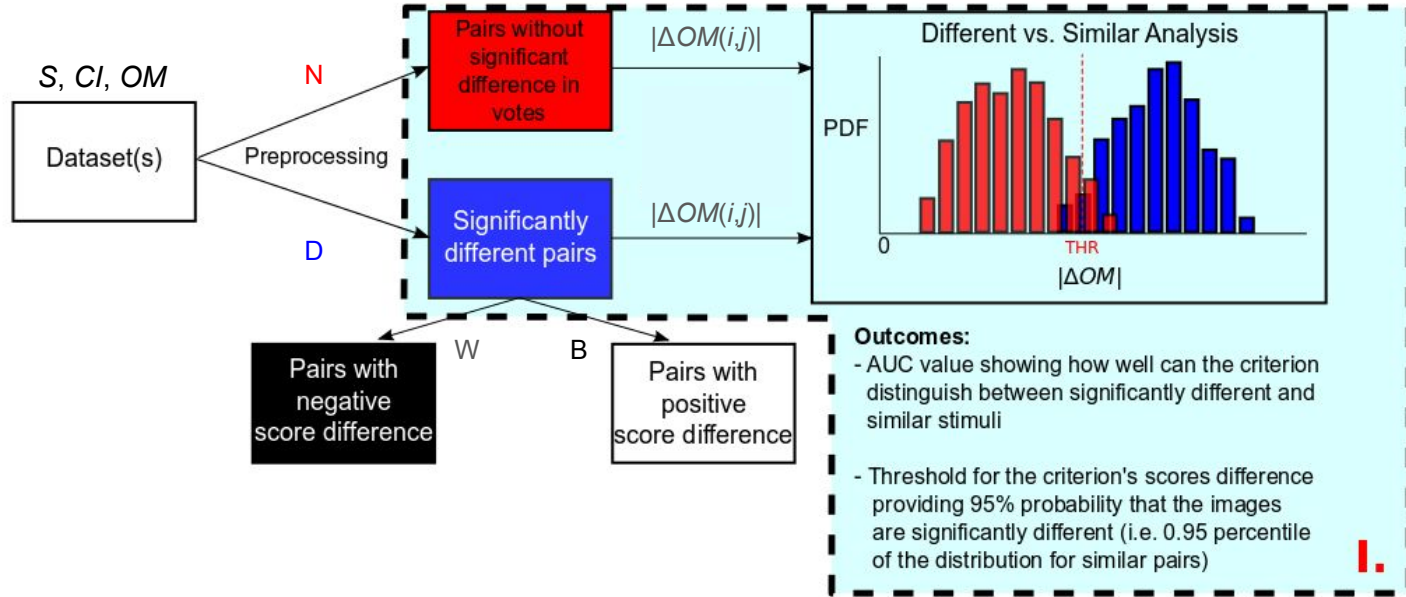
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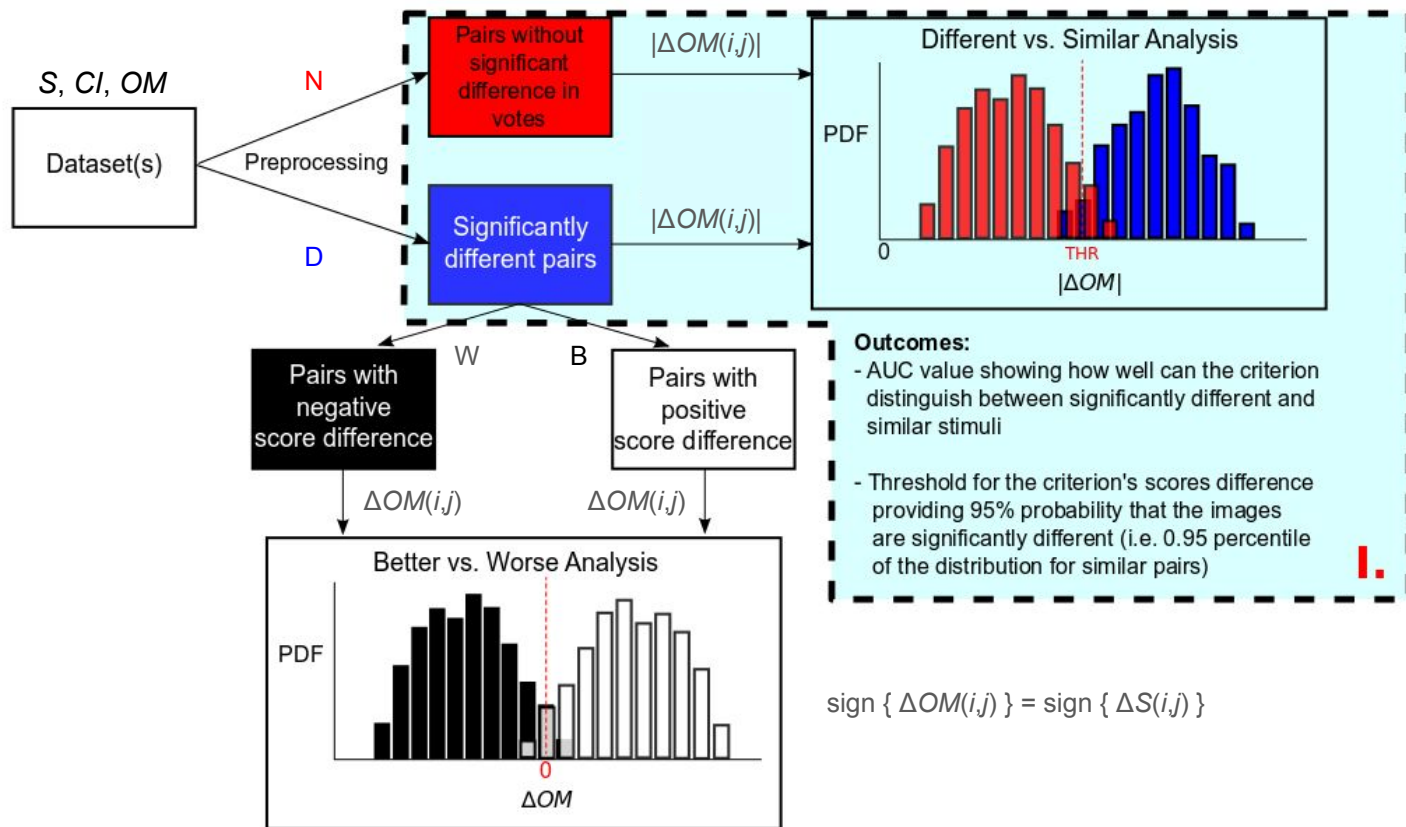
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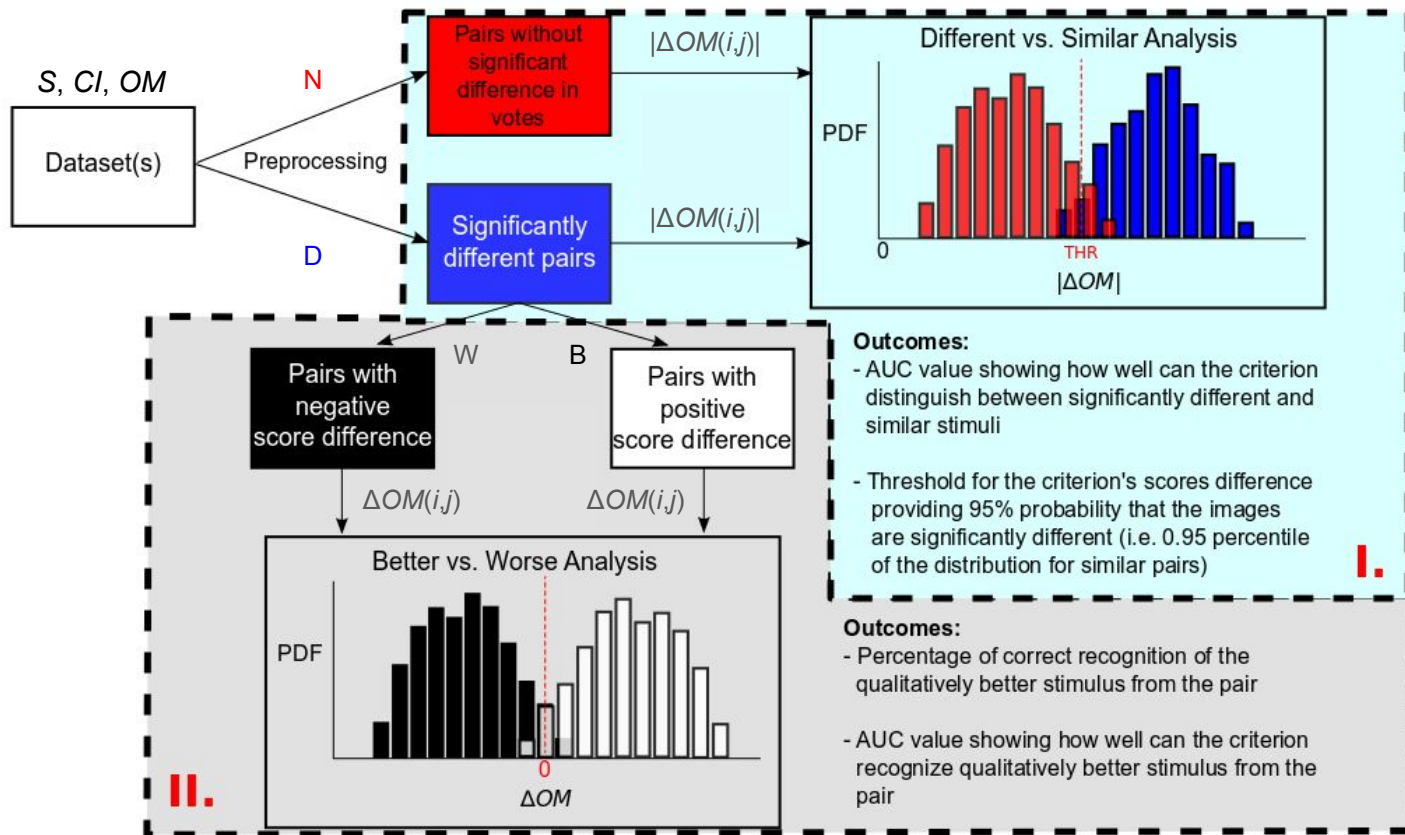
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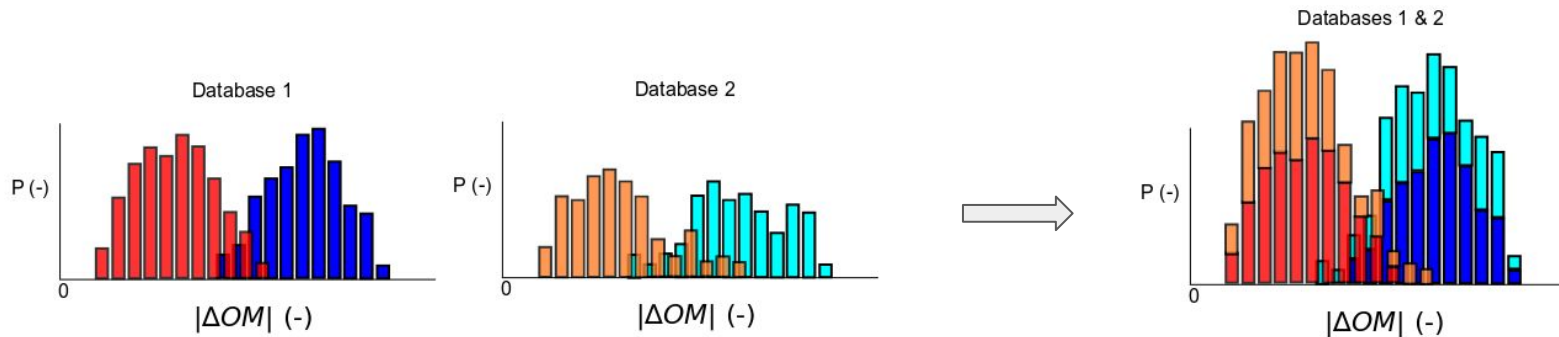
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- Moreover...
  - Universality towards the subjective procedure, scale, and format of the ground-truth data
  - Allows for simple numerical comparisons and testing of statistical significance
  - High statistical power (due to the pair-wise approach)
  - Enables simple and meaningful combination of the data coming from multiple datasets

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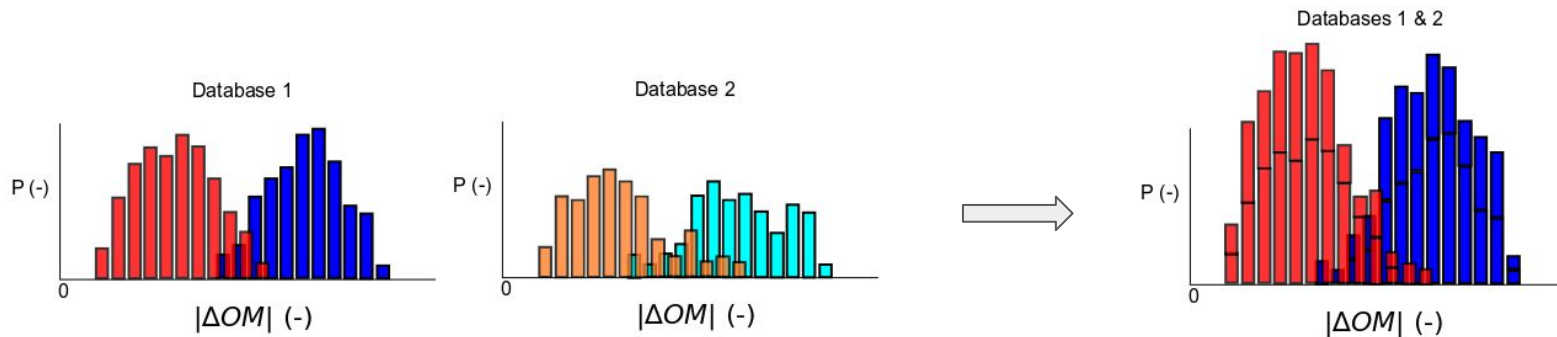
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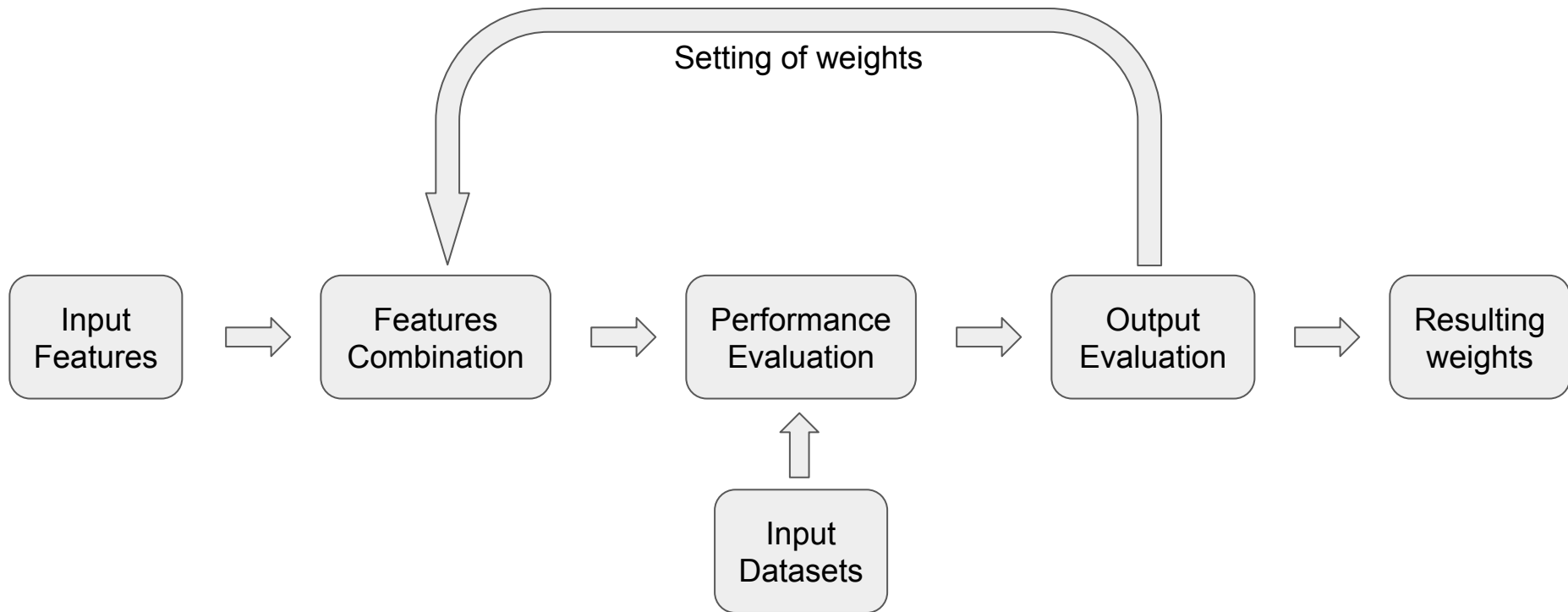


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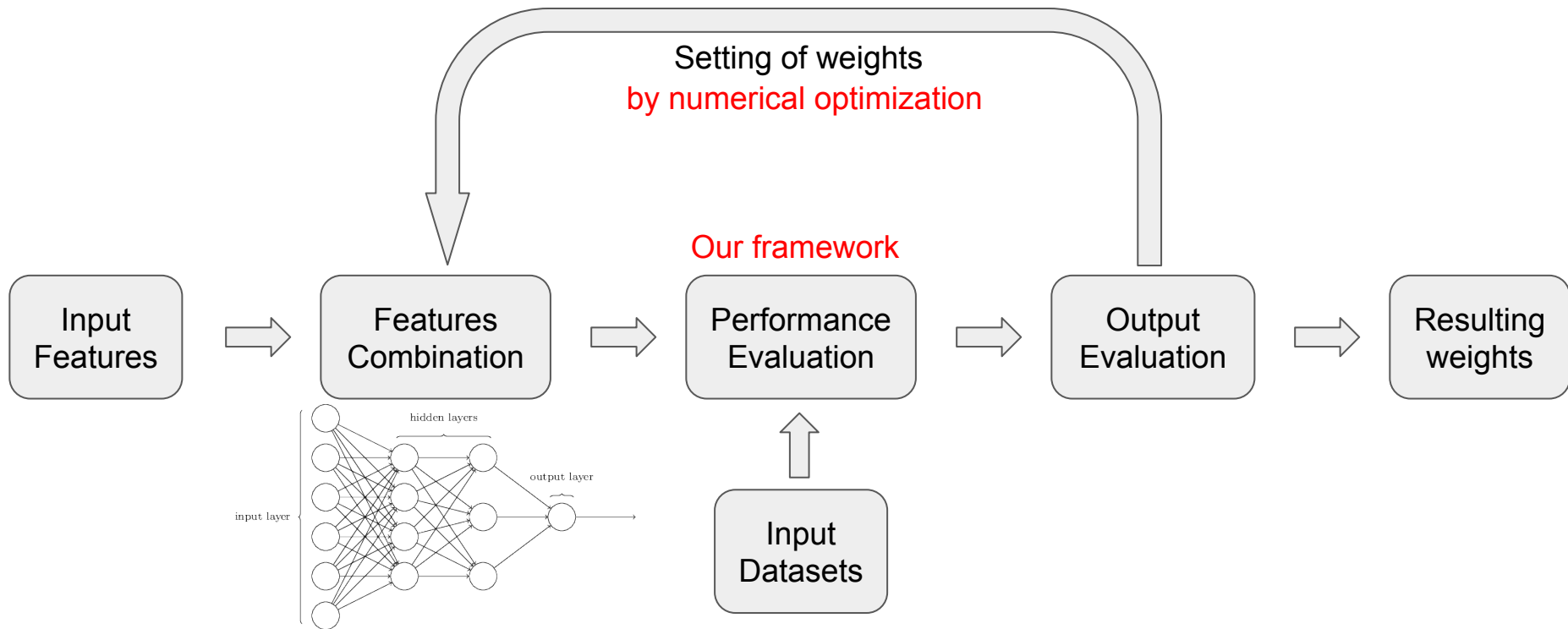
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  - High statistical power (due to the pair-wise approach)
  - **Enables simple and meaningful combination of the data coming from multiple datasets**
    - No inter-experiment mapping necessary
    - Overall performance can be easily determined
    - Increase of number of training/testing points in orders of magnitude - deep learning etc.

# Using the framework for objective metrics training





# Using the framework for objective metrics training

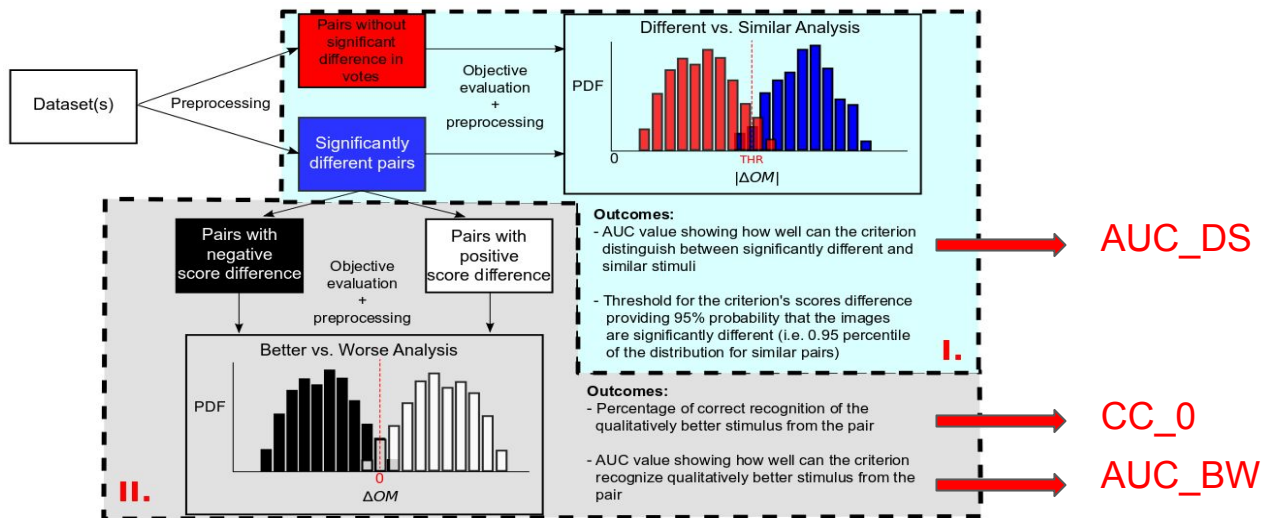


# Preliminary results

- Publicly available VMAF (Video Multi-Method Assessment Fusion) package
  - VMAF features (VIF on 4 scales, Detail Loss, Motion)
- 18 datasets (9 used for training, 9 for testing)
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=====

Custom Neural Network:

-----Test set-----  
AUC\_DS = **0.7869**  
AUC\_BW = **0.9550**  
CC\_0 = **0.8963**

-----Test + Train sets-----  
AUC\_DS = **0.7646**  
AUC\_BW = **0.9551**  
CC\_0 = **0.8957**

VMAF (trained on one of the datasets):

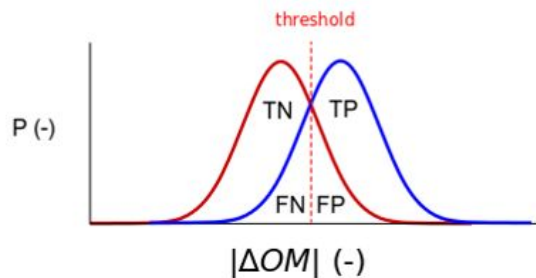
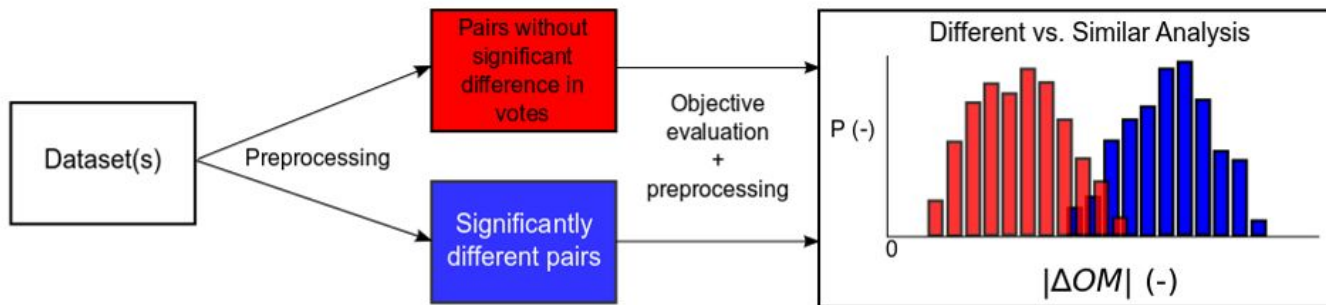
-----Test set-----  
AUC\_DS = 0.7586  
AUC\_BW = 0.9490  
CC\_0 = 0.8951

-----Test + Train sets-----  
AUC\_DS = 0.7230  
AUC\_BW = 0.9469  
CC\_0 = 0.8954

Thank you for your attention!



# ROC Analysis

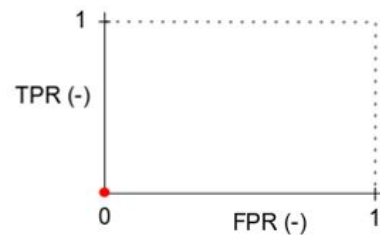
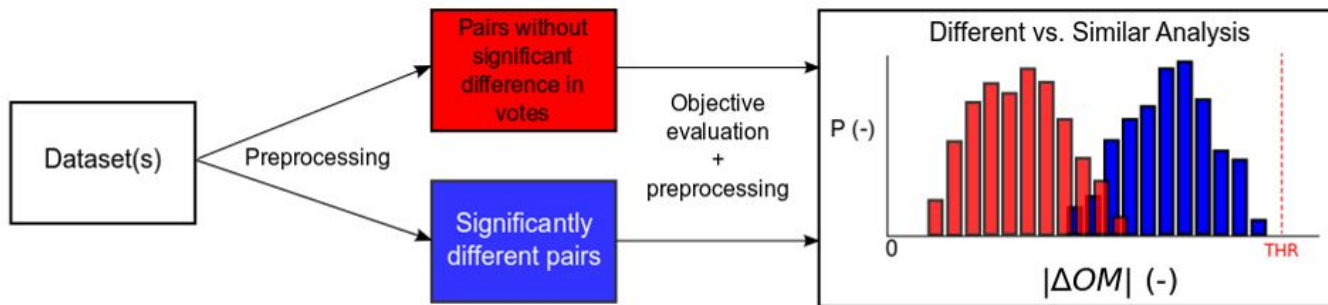


TN - true negative  
TP - true positive  
FN - false negative  
FP - false positive

True positive rate  
 $TPR = TP / (TP + FN)$

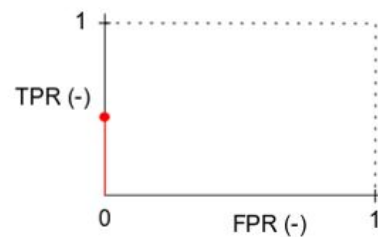
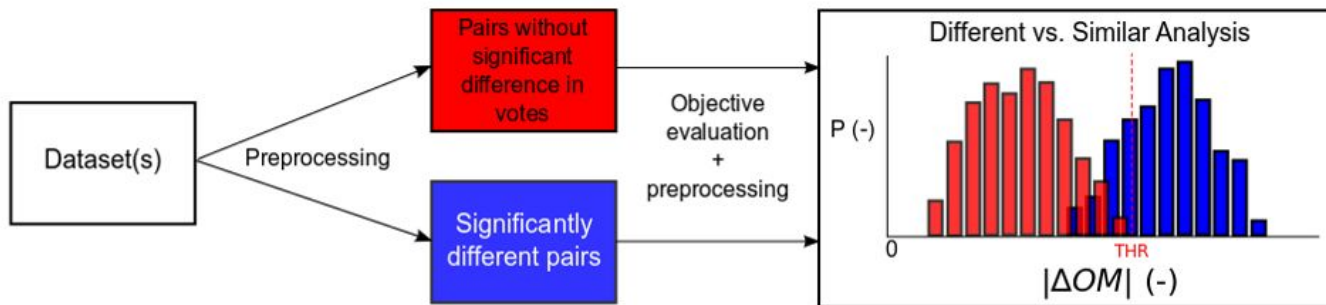
False positive rate  
 $FPR = FP / (FP + TN)$

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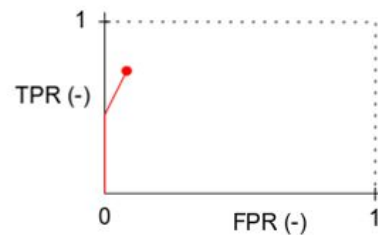
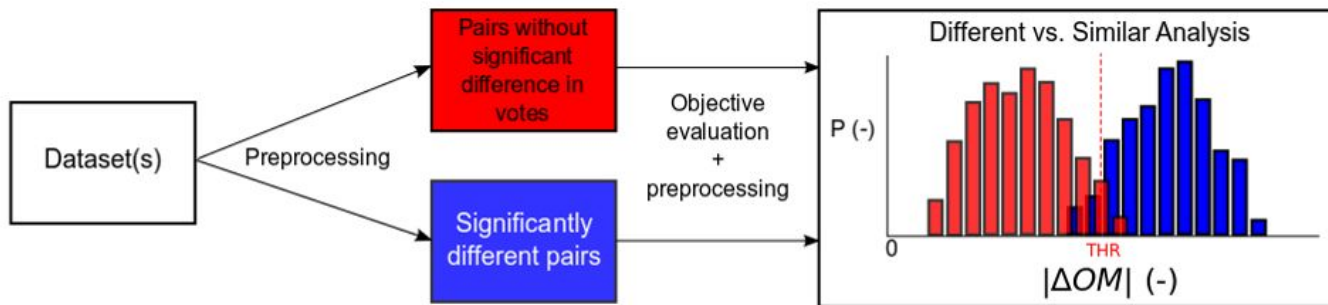




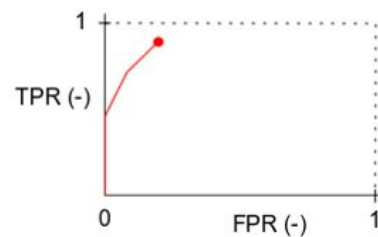
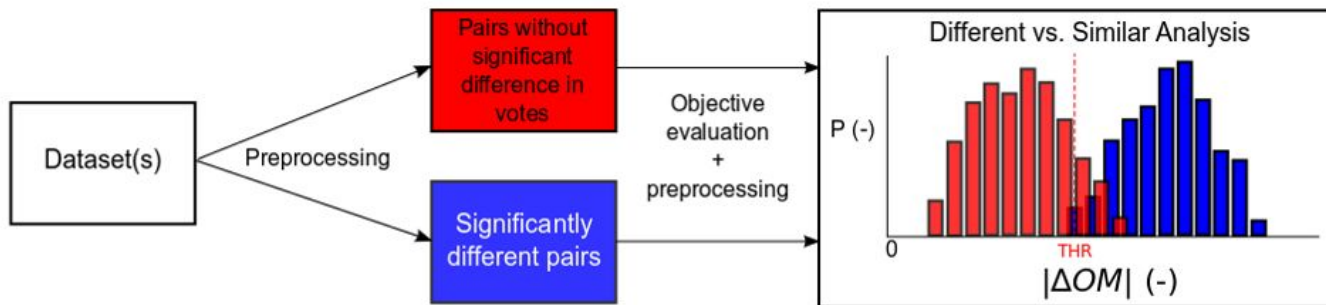
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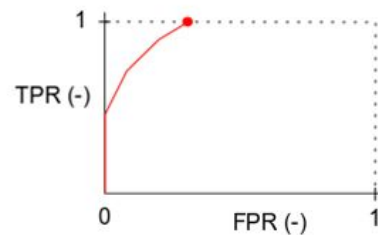
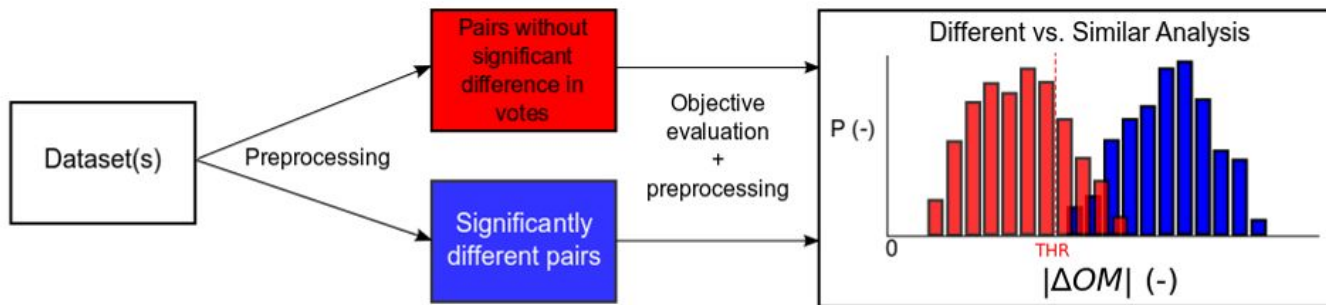
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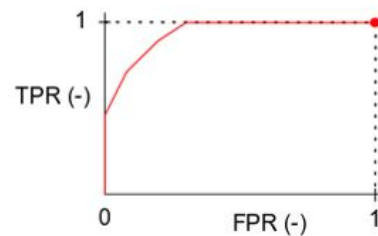
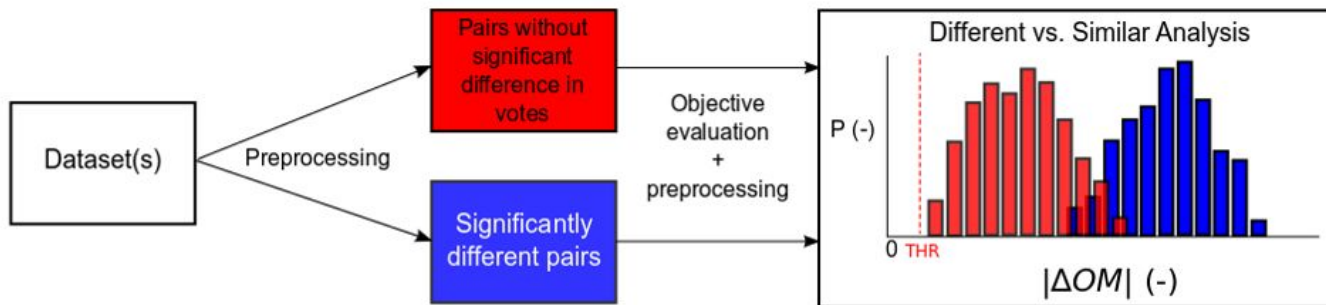
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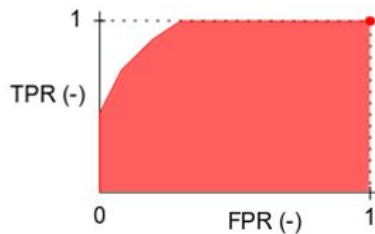
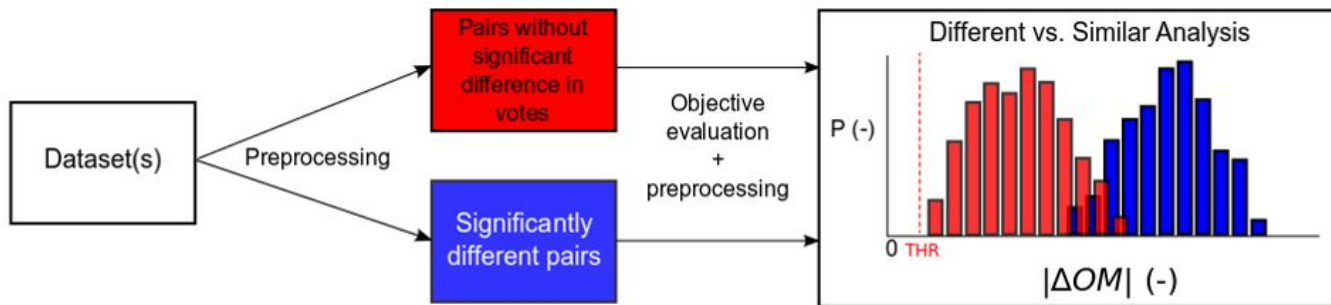
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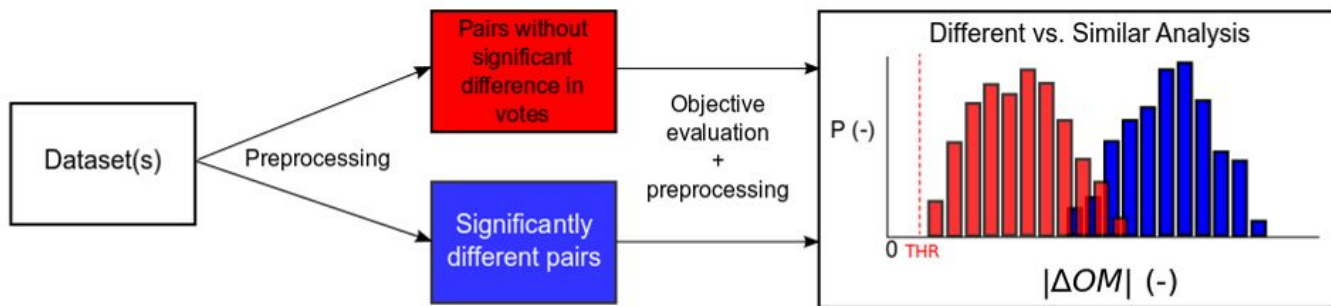
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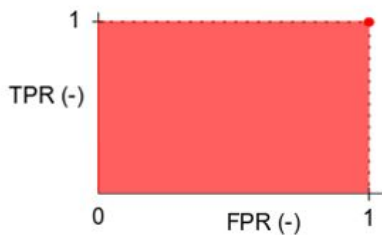
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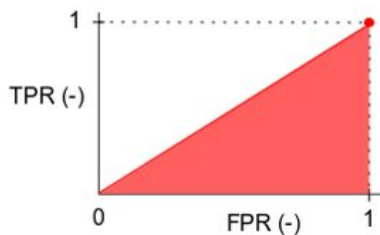
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AUC = 1



AUC = 0.5



AUC = 0.85

