Data Analysis Proposition

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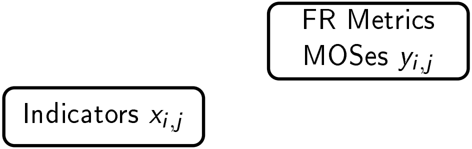
June 11, 2012

Data Flows



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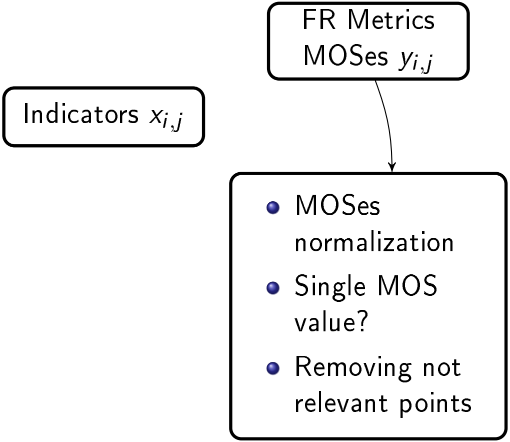
FR Metrics
MOSes $y_{i,j}$
Indicators $x_{i,j}$
MOSes normalization
Single MOS value?
Removing not relevant points

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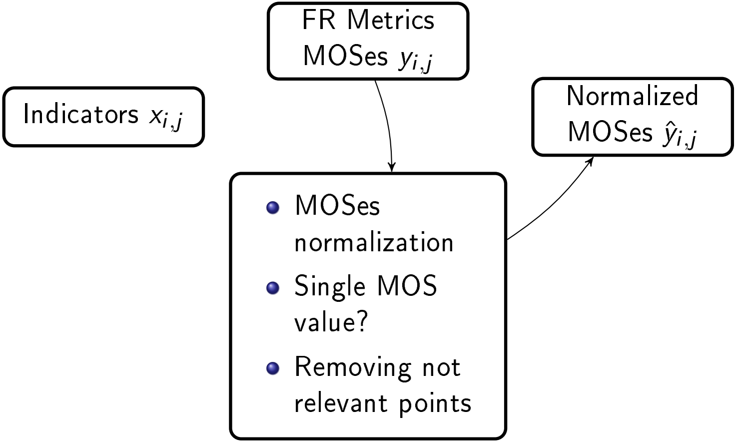
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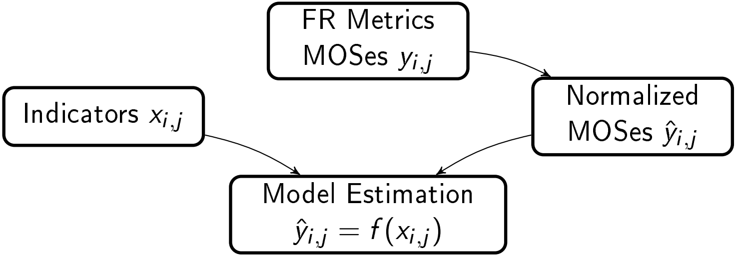
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$\hat{y}_{i,j} = f(x_{i,j})$

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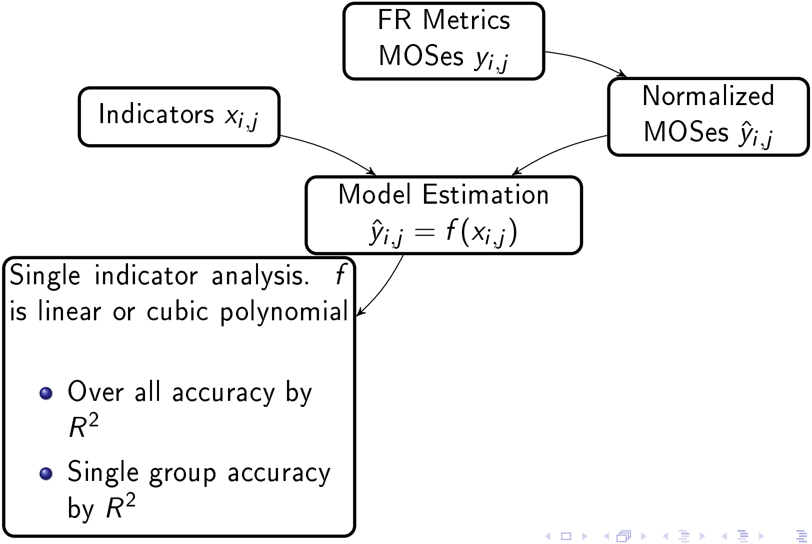
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Single indicator analysis. f is linear or cubic polynomial
Over all accuracy by R^2
Single group accuracy by R^2

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- Over all accuracy by R^2
- Single group accuracy by R^2

Multiple indicators analysis. f is linear or linear with interactions

- Indicator accuracy by p-value
- Overall model accuracy by adjust R^2

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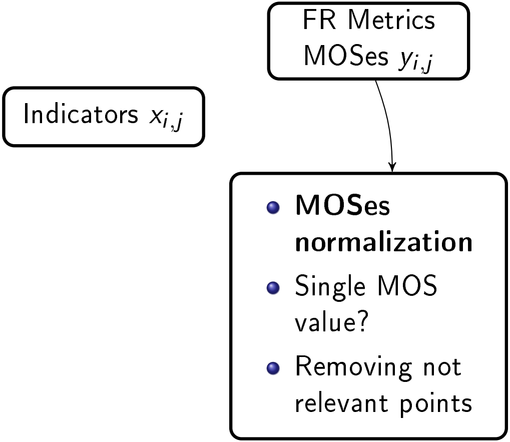
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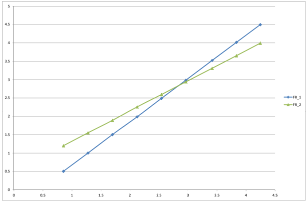
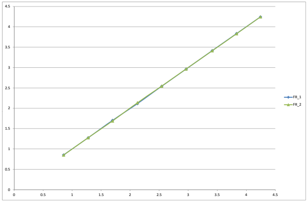
- For HDTV it was set of subjective MOSes, for JEG-Hybrid it cannot be assumed
- Mean MOS of all metrics works the best probably

Example

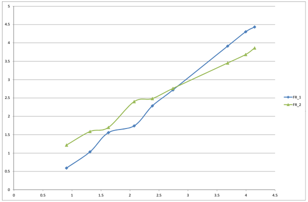


Input data



Normalized metrics

Example with Errors



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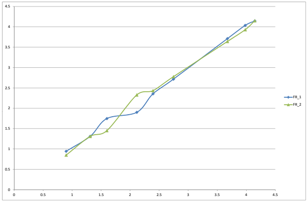
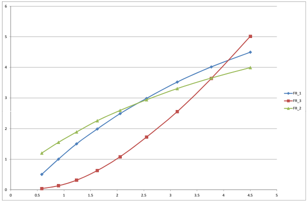


Normalized metrics

Example Non Linear



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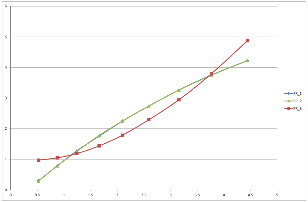

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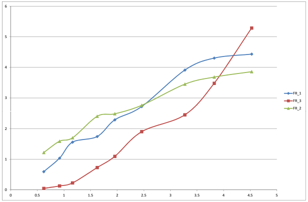

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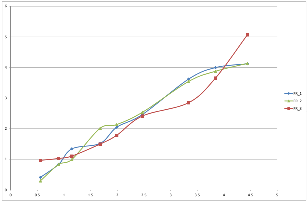

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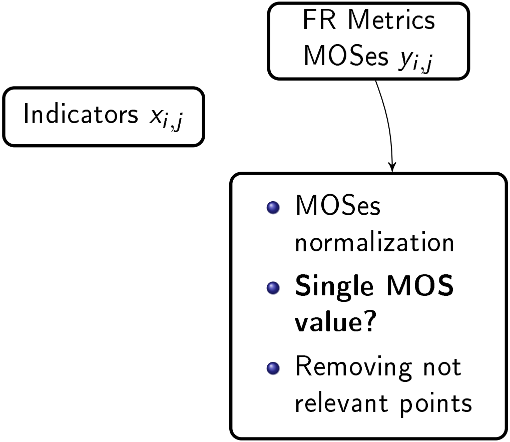
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Single MOS or Multiple MOSes

- More points more information
- An alternative solution is regression including errors
- Is an error for 3-4 points really meaning full?
- If all points are used a perfect metric has R^2 different from 1 since the metrics inaccuracy makes the target function irrelevant

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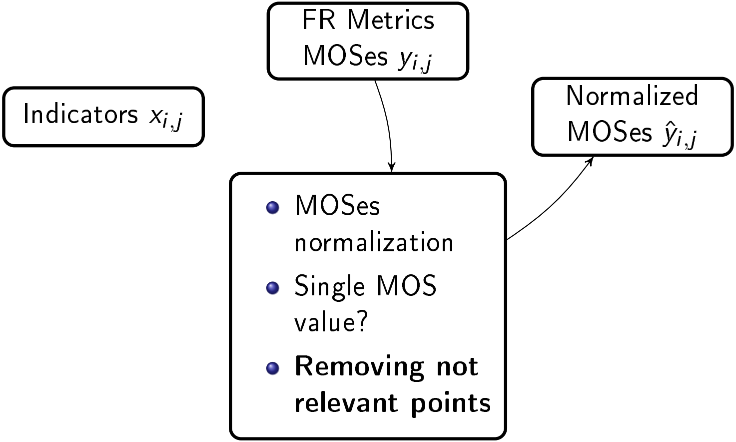
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Removing not Relevant Points

- $|MOS_{i,1} - (aMOS_{i,2} + b)| > \epsilon$ is changed to $|\hat{y}_{i,1} - \hat{y}_{i,2}| > \epsilon$.
- For many metrics PVS_j is removed if $\max_j |\hat{y}_{i,j} - \hat{y}_{i,j}| > \epsilon$
- What should be ϵ value?
- Typical subjective experiment error? Which is?

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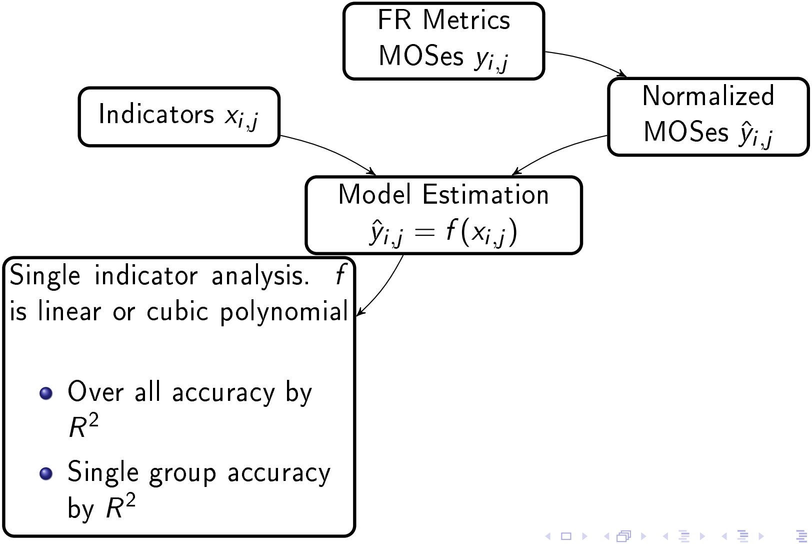
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PVS Grouping

- An indicator can work just for some PVSes (e.g. frame rate change only)
- Single PVS can be a member of many different groups
- Each analysis is performed on each group including all data
- Group of PVSes is a set of i indexes I_k

Analysis

Let us consider metric number 1

- Estimate a and b of a linear fit $\hat{y}_{i,j} = ax_{i,1} + b$ for $i \in I_k$ and all j and k
- Calculate R^2 for the obtained fit
- $x_{\cdot,1}$ normalization by $\frac{x_{i,1} - \bar{x}_1}{\sigma_{x_{i,1}}}$ where $\sigma_{x_{i,1}}$ is the standard deviation
- Estimate a cubic fit for $\hat{y}_{i,j} = \sum_{l=0}^{3} a_l x_{i,1}^l$ for $i \in I_k$ and all j and k
- Chucking p-values of a_l - is the metric non linear?
- Calculate R^2 for the obtained fit

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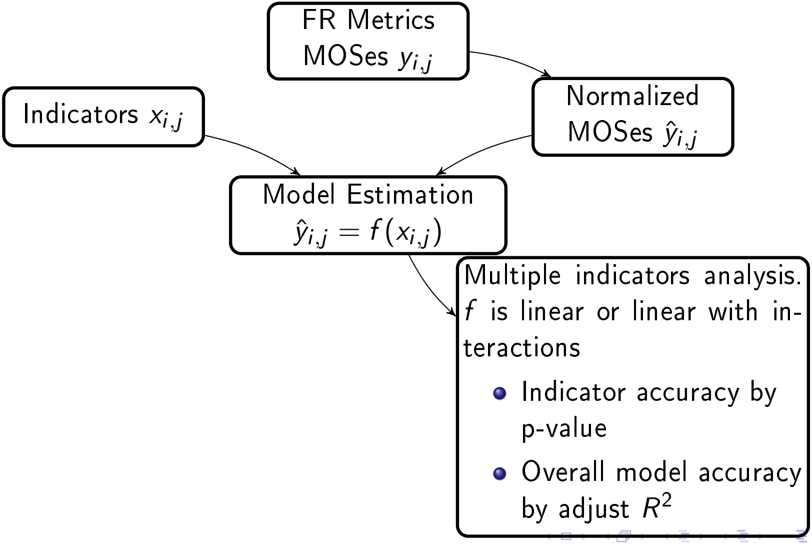
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Multiple indicators analysis. f is linear or linear with interactions
Indicator accuracy by p-value
Overall model accuracy by adjust R^2

Analysis

- $x_{\cdot,1}$ normalization by $\frac{x_{i,1}-\bar{x}_1}{\sigma_{x_{i,1}}}$ where $\sigma_{x_{i,1}}$ is standard deviation
- Estimate a linear fit $\hat{y}_{i,j} = \sum_l a_l x_{i,b_l} + b$ for $i \in I_k$ and all j, k and all possible combinations of b_l values - if possible $\hat{y}_{i,j} = a_1 x_{i,1} + a_2 x_{i,2} + b$; $\hat{y}_{i,j} = a_1 x_{i,1} + a_2 x_{i,3} + b$; $\hat{y}_{i,j} = a_1 x_{i,2} + a_2 x_{i,3} + b$; $\hat{y}_{i,j} = a_1 x_{i,1} + a_2 x_{i,2} + a_3 x_{i,3} + b$
- First step is p-values analysis: is particular indicator statistically important?
- Removing not statistically important indicators and than adjust R^2 computation

Analysis

- Metrics "cooperation" $\hat{y}_{i,j} = a_0 + a_1 x_{i,1} + a_2 x_{i,2} + a_3 x_{i,1} x_{i,2}$ for $i \in I_k$ and all j and k
- First step is p-values analysis: is particular indicator statistically important? Looking especially on the metrics products coefficients
- Removing not statistically important indicators and than adjust R^2 computation