



MRMR

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Maximum Relevancy, Minimum Redundancy

Michael Matějů

AI Squad

July 28, 2023



Outline

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Motivation

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- Mirek Pavelka point this algorithm to me
- Recent popularity of the algorithm due to UBER's paper (2019).



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Introduction

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Feature selection methods allow you to choose the best features in your dataset, with respect to some criteria. Feature selection methods can be divided into three families:

- Filter Methods: Feature selection is made as part of the pre-processing, that is, before we train a model. We filter out features that perform poorly based on some criteria (e.g. correlation).
- Wrapper Methods: Iteratively choose a subset of features, train your model, and choose the best combination. Very time consuming.
- Embedded Methods: Embedded methods take advantage of the feature importance estimations which are embedded in the algorithm. E.g. Random Forest.



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Cheat Sheet

MRMR

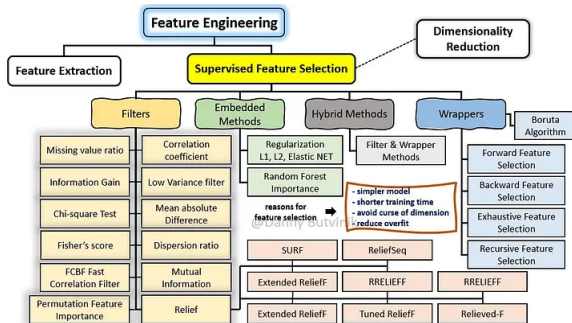
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MRMR works iteratively. At each iteration, it identifies the best feature (according to a rule) and adds it to the basket of selected features. Once a feature goes into the bucket, it cannot ever come out.

In each iteration i a score is computed for each feature f according to formula:

$$score_i(f) = \frac{relevance(f|target)}{redundancy(f|features\ selected\ until\ (i-1))} ,$$

where we have to specify the relevancy and redundancy functions.



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Feature importance

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There are couple of variants to calculate the feature importance from the original UBER paper. For discrete features:

- Mutual Information Difference (MID):

$$f^{MID}(X_i) = I(Y, X_i) - \frac{1}{|S|} \sum_{X_s \in S} I(X_s, X_i)$$

- Mutual Information Quotient (MIQ):

$$f^{MID}(X_i) = I(Y, X_i) / \left(\frac{1}{|S|} \sum_{X_s \in S} I(X_s, X_i) \right)$$



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For continuous features:

- F-test Correlation Difference (FCD):

$$f^{MID}(X_i) = F(Y, X_i) - \frac{1}{|S|} \sum_{X_s \in S} \rho(X_s, X_i)$$

- F-test Correlation Quotient (FCQ):

$$f^{MID}(X_i) = F(Y, X_i) / \left(\frac{1}{|S|} \sum_{X_s \in S} \rho(X_s, X_i) \right)$$

where ρ is Pearson correlation.



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Another extensions:

- RDC algorithm for redundancy function (The randomized dependence coefficient)
- Model-based Feature importance for relevance:
 - Random Forest Correlation Quotient
 - Random Forest RDC Quotient
 - Pure Random Forest

From benchmarks, RF variances are good if down-stream model is Random Forest. FCQ is pretty close and works on more models.



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Example

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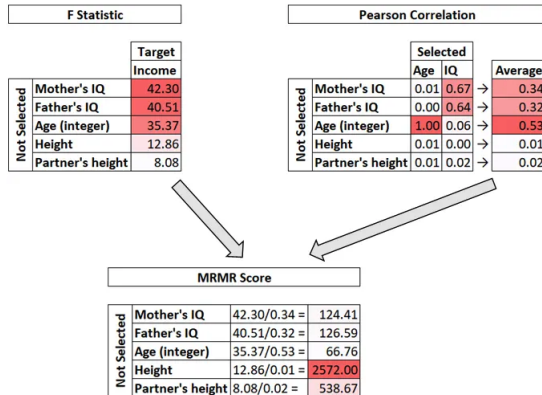


Illustration of what happens at iteration 3. [Figure by Author]



The End

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Thank you for your attention and patience.