ATTRIBUTE SELECTION IN SEISMIC FACIES CLASSIFICATION: APPLICATION TO A GULF OF MEXICO 3D SEISMIC SURVEY

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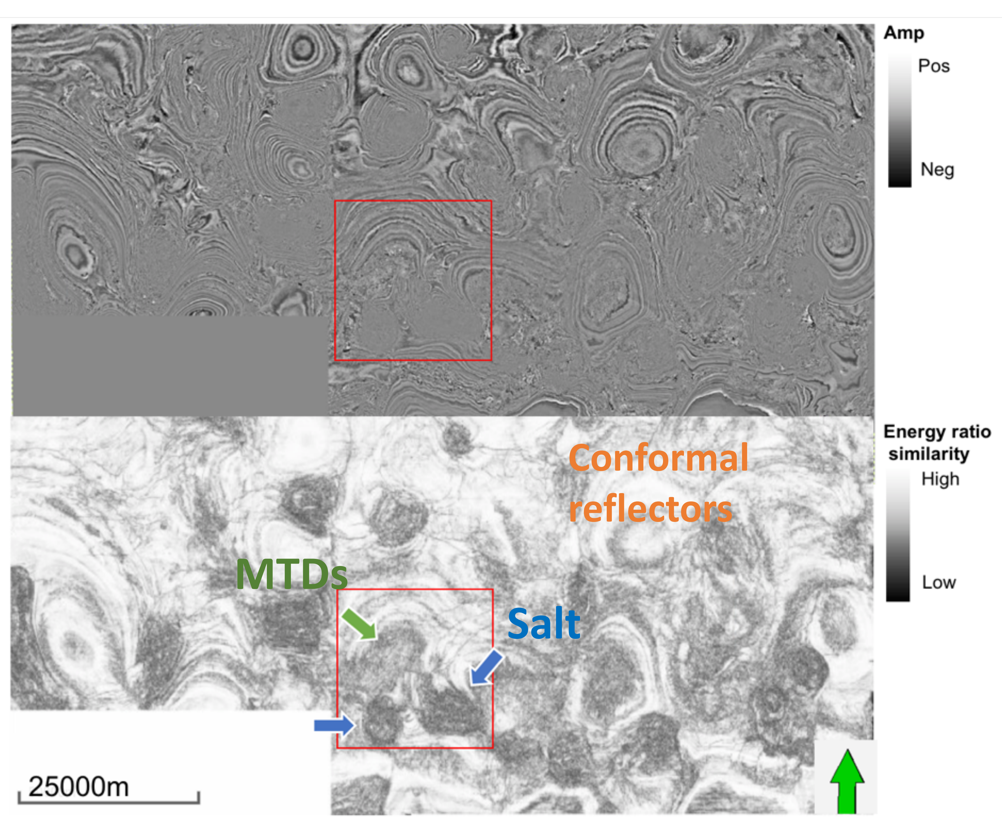
Abstract

Selecting appropriate attributes is a crucial part of the seismic facies classification workflow for reducing computational cost and reasonable model building. For supervised learning, the best attribute subset can be built by selecting input attributes that identify and differentiate the output classes and avoiding redundant attributes that are similar to each other. In this study, multiple attributes are tested to classify salt diapirs, mass transport deposits (MTDs) and the conformal reflector "background" for a 3D seismic marine survey acquired on the northern Gulf of Mexico shelf. We analyze attribute-to-attribute correlation and the correlation between the input attributes to the output classes to maximize relevance and minimize redundancy in attribute selection. We find that amplitude and texture attribute families are able to differentiate salt and MTDs. Multivariate analysis using filter, wrapper and embedded algorithms rank the attributes by importance, indicating the best attribute subset for a specific classification. We show that attribute selection algorithms for supervised learning can not only reduce computational cost but also enhance the performance of the classification.

Case study: GOM survey

- **Attribute selection to differentiate salt, MTDs, and conformal reflectors**

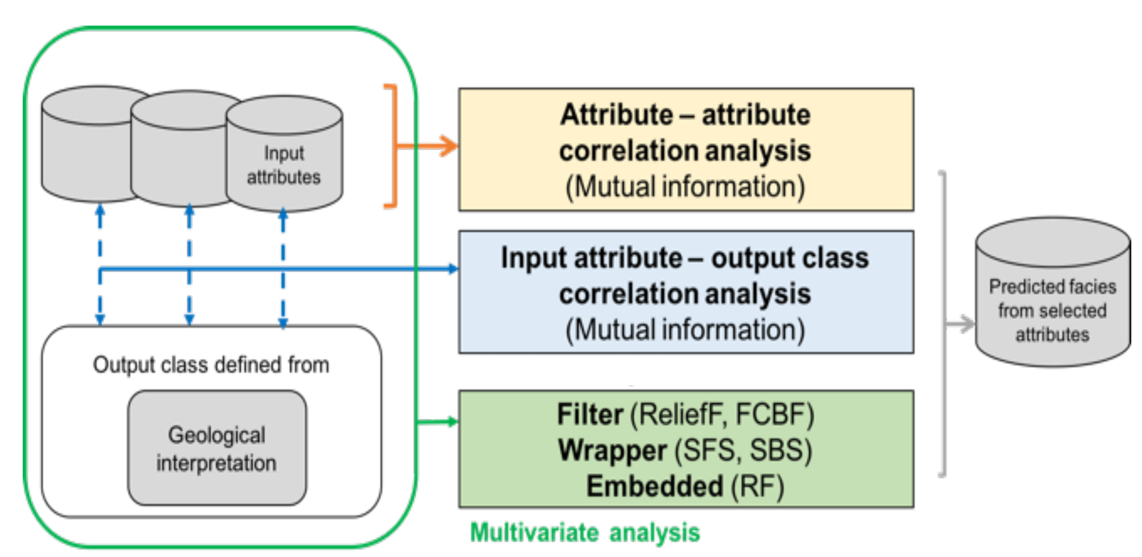


- **Seismic attribute families and 20 attributes**

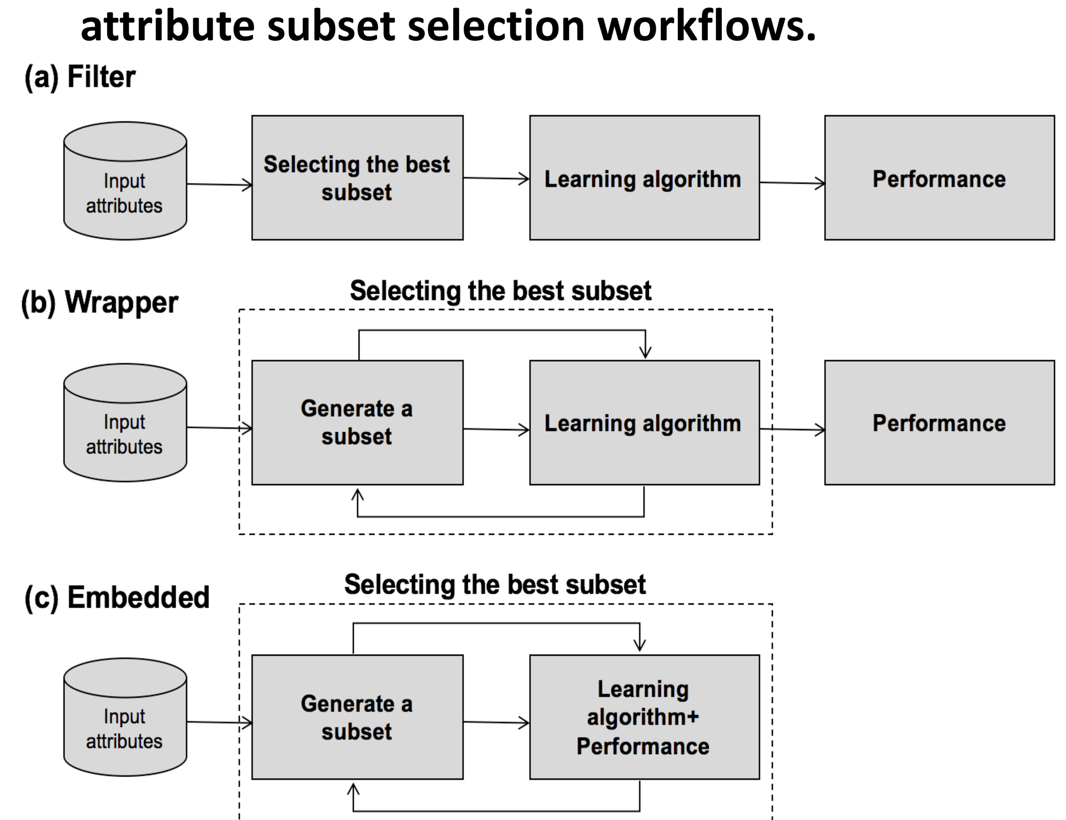
Attribute families	Seismic attributes
Amplitude attributes	RMS amplitude, total energy, relative acoustic impedance
Instantaneous attributes	Instantaneous envelope, instantaneous frequency, instantaneous phase
Geometric attributes	Variance, dip magnitude, dip azimuth, most-positive curvature, most-negative curvature, curvedness, aberrancy magnitude, aberrancy azimuth
Texture attributes	Chaos, GLCM entropy, GLCM homogeneity
Spectral attributes	Peak magnitude, peak frequency, peak phase

Methodology

- **Workflow to select the best subset of attributes.**



- **Schematic diagram summarizing the the steps from the (a) filter, (b) wrapper and (c) embedded attribute subset selection workflows.**



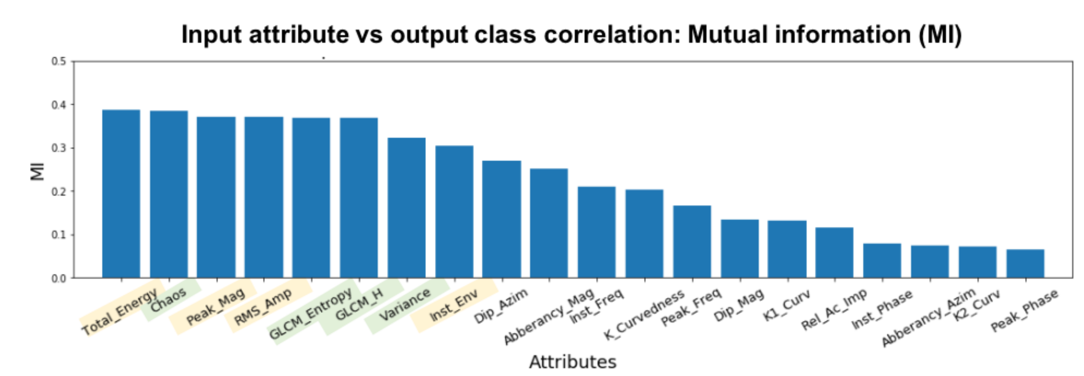
Results

- **Attribute-to-attribute correlation analysis**

Attribute – attribute correlation analysis

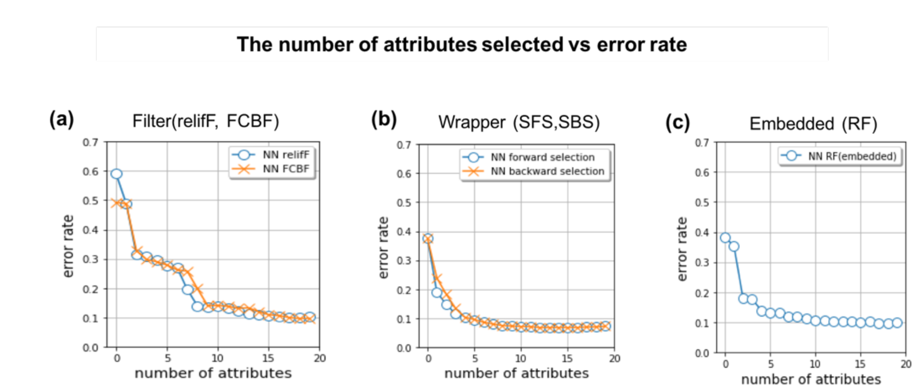
Correlation measure	Attributes highly correlated with the other attributes (corr. coeff. > 0.5)
Mutual information	RMS amp. – Total energy (0.9)
	GLCM entropy – GLCM homogeneity (0.85)
	Inst. envelope - Peak magnitude (0.74)
	RMS amp. - Inst. envelope (0.72)
	Total energy - Inst. envelope (0.71)
	RMS amp. – Peak magnitude (0.69)
	Total energy - Peak magnitude (0.68)
	Variance - GLCM homogeneity (0.55)
	Relative Acoustic impedance - Inst. phase (0.55)
	Variance - GLCM entropy (0.50)

- **Relationships between a single input attribute and the three desired output**



- **Selected attribute subsets using filter (ReliefF, FCBF), wrapper (NN) and embedded (RF) methods**

Filter	ReliefF		Peak_Phase	Peak_Freq	Total_Energy	Rel_Ac_Imp	Inst_Env	Inst_Freq	Inst_Phase	Variance	Dip_Mag	Dip_Azim
	FCBF		Peak_Freq	Peak_Phase	RMS_Amp	Total_Energy	Rel_Ac_Imp	Inst_Env	Inst_Freq	Inst_Phase	Variance	Dip_Mag
Wrapper	SFS	NN	Total_Energy	Chaos	Abberancy_Mag	Inst_Freq	Variance	Dip_Azim	Dip_Mag	Abberancy_Azim	Peak_Freq	K1_Curv
	SBS	NN	Total_Energy	Variance	Dip_Mag	Inst_Freq	Abberancy_Mag	Dip_Azim	Abberancy_Azim	Chaos	Peak_Freq	K1_Curv
Embedded	RF		Total_Energy	Peak_mag	Chaos	RMS_Amp	Abberancy_Mag	GLCM_h	GLCM_Entropy	Inst_Env	Variance	Inst_Freq

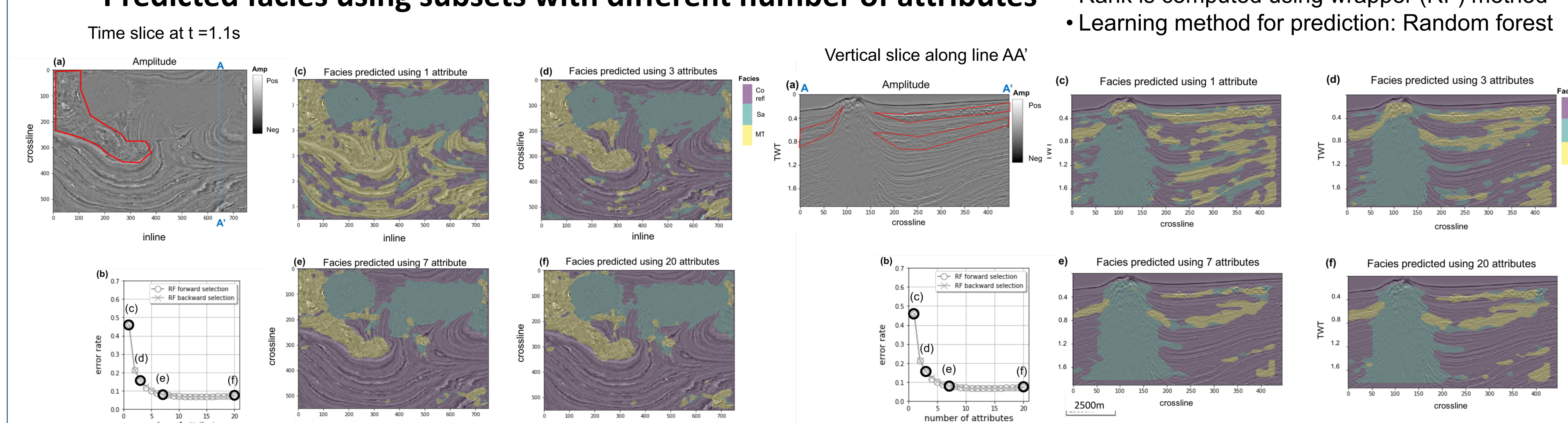


→ The number of attributes included in the attribute subset versus error rate. Attributes in the subset were selected using (a) filter methods (ReliefF, FCBF), (b) wrapper methods (SFS, SBS), and (c) an embedded method (RF). Each attribute subset was validated using neural network (NN) classifiers.

Results : prediction using attribute subset

- **Predicted facies using subsets with different number of attributes**

- Rank is computed using wrapper (RF) method
- Learning method for prediction: Random forest



Conclusion

- We need to analyze all attributes together using a framework which can quantitatively rank the attributes to build the most effective subset.
- In this example, facies not used in training such as turbidites, faults, overpressured shale, and seismic noise can be misclassified.
- Understanding each seismic attribute's characteristic is crucial to implement automated facies classification and to aid rendering of a seismic volume where the interpreters target.

Reference

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