Transformation Based Feature Selection for Human Emotion

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Abstract

We pose feature selection as a feature transformation problem by solving an optimization problem for a projection-based criterion with a sparsity inducing norm penalty term. This allows us to solve a convex optimization problem to reduce the dimensionality of the data while maintaining the meaning of the original features. Through the optimization, the high dimensional feature set is projected into a lower dimensional space that optimizes the given criterion, while simultaneously forcing whole rows of the projection matrix to zero, resulting in a projection based on a subset of the feature set.

We apply this to data from a psychophysiological experiment designed to evaluate physiological responses to emotionally evocative stimuli. Physiological responses were recorded from a variety of sensor modalities including electrocardiogram (ECG), respiration, electrodermal activity (EDA), finger pulse (FP), body movement, and pupil diameter. The resultant feature subset both lies in a reduced dimension space and provides insight to understanding the autonomic mechanisms of human emotion.

Technical Approach

Goals:
- Reduce dimensionality
- Maintain feature meaning
- Learn relationships among features
- Retain label information in features
- Eliminate redundant, noisy features

Hilbert-Schmidt Independence Criterion measures independence using the Hilbert-Schmidt Norm of a cross-covariance operator in a Reproducing Kernel Hilbert Space.

Probabilities are unknown, so the empirical estimation is as below, for data X and labels Y.

$$HSIC(X,Y) = \frac{1}{n^2} tr(KHLH)$$

\# of samples

$$K,H,L \in \boldsymbol{R}^n$$

Gaussian Kernel in the transformed feature space

Feature vector for subject i

$$K_{ij} = k(x_i, x_j) = e^{\frac{1}{2}\sum_k^d w_k^T (x_i - x_j)(x_i - x_j)^T w_k}$$

Kernel Function on the labels

$$L_{ij} = l(y_i, y_j) = \delta(y_i, y_j) = \begin{cases} 1 & y_i = y_j \\ 0 & y_i \neq y_j \end{cases}$$

Centering Matrix

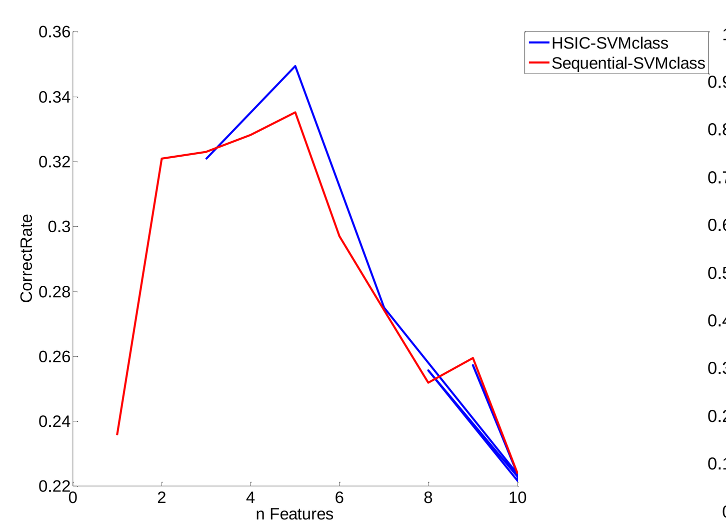
$$H = I - \frac{1}{n} 1_n 1_n^T$$

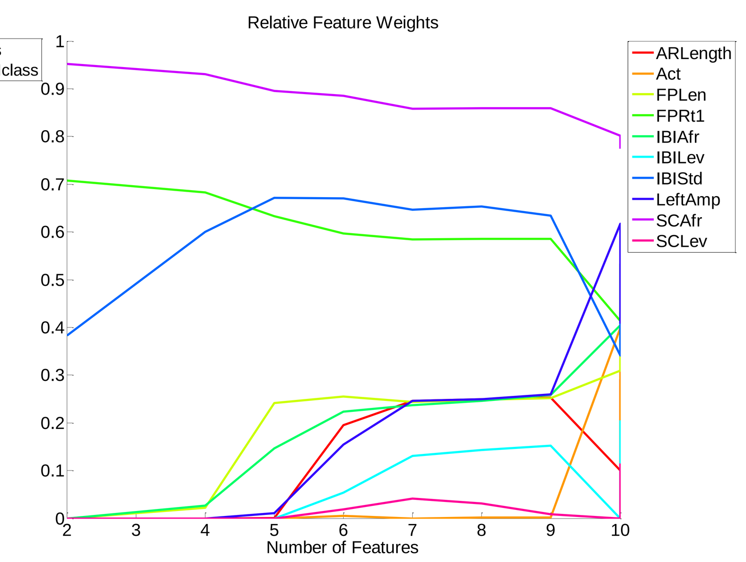
Data Collection

- 32 subjects were each presented with 24 sound and image stimuli
- Stimuli are expected to evoke one of five emotions: Amusement, Fear, Disgust, Sadness, or Anger
- Physiology was collected during the entire experiment
- Current analysis uses features extracted with CPSLAB, averaged across stimulus class and standardized within subject

Features	
ARLength	Abdominal respiration line length for a window beginning at stimulus onset
Act	Gross body movement line length for a window beginning at stimulus onset
FPLen	Line length of the finger pulse signal for a window beginning at stimulus onset
FPRt1	Finger pulse response from the first low point for a window beginning at stimulus onset
IBIAfr	Interbeat interval (derived from ECG) area to full recovery for a window beginning at stimulus onset
IBILev	Interbeat interval (derived from ECG) level for a window beginning at stimulus onset
IBIStd	Standard deviation of Interbeat interval (derived from ECG) for a window beginning at stimulus onset
LeftAmp	Left pupil diameter peak amplitude
SCAfr	Area to full recovery for the electrodermal activity signal for a window beginning at stimulus onset
SCLev	Level of the electrodermal activity signal for a window beginning at stimulus onset

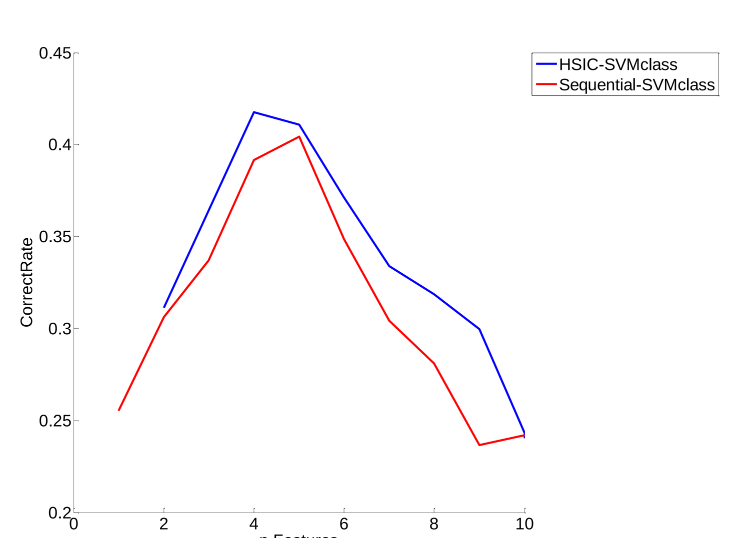
Results- Sounds

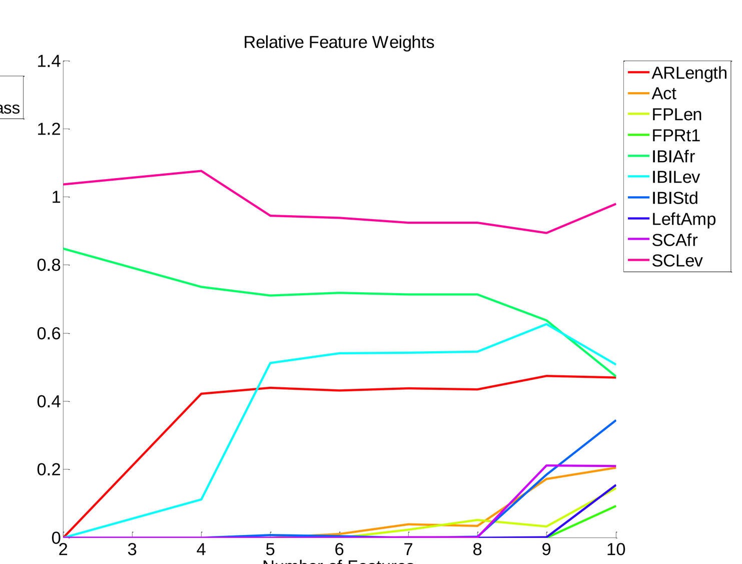




Transform Based Feature Selection				Sequential Forward Search			
Selected Features	Correct Rate	Sensitivity	Specificity	Selected Features	Correct Rate	Sensitivity	Specificity
[4 9]	0.31313	0.193	0.8665	[4 7]	0.31487	0.43033	0.78675
[4 7 9]	0.36247	0.372	0.79383	[4 5 9]	0.36833	0.51833	0.75108
[3 4 7 9]	0.376	0.32633	0.78017	[4 5 7 9]	0.37947	0.54333	0.76933
[3 4 5 7 9]	0.41907	0.39767	0.78275	[4 5 7 8 9]	0.36393	0.424	0.77133
[3 4 5 7 8 9]	0.37013	0.32967	0.77042	[2 4 5 7 8 9]	0.31947	0.35867	0.79325
[1 3 4 5 7 8 9]	0.35353	0.40633	0.82733	[2 3 4 5 7 8 9]	0.3028	0.25567	0.74483
[1 3 4 5 6 7 8 9]	0.3536	0.392	0.83458	[2 3 4 5 6 7 8 9]	0.31413	0.32933	0.74817
[1 3 4 5 6 7 8 9 10]	0.34953	0.33033	0.82633	[1 2 3 4 5 6 7 8 9]	0.3262	0.38567	0.81658
[1 2 3 4 5 6 7 8 9 10]	0.30487	0.30733	0.79175	[1 2 3 4 5 6 7 8 9 10]	0.3044	0.306	0.79067

Results- Images





Transform Based Feature Selection				Sequential Forward Search			
Selected Features	Correct Rate	Sensitivity	Specificity	Selected Features	Correct Rate	Sensitivity	Specificity
[5 10]	0.39828	0.33207	0.89647	[5 6]	0.31531	0.51966	0.84845
[1 5 6 10]	0.4669	0.58517	0.87853	[3 5 9]	0.34276	0.50793	0.80957
[1 5 6 7 10]	0.43655	0.4931	0.89138	[5 6 7 10]	0.45476	0.47034	0.91897
[1 2 5 6 7 10]	0.38952	0.53414	0.80276	[3 5 6 7 10]	0.44034	0.46172	0.87103
[1 2 3 5 6 9 10]	0.39062	0.52655	0.79147	[3 4 5 6 7 10]	0.36048	0.42138	0.84983
[1 2 3 5 6 7 9 10]	0.38641	0.52103	0.73672	[2 3 4 5 6 7 10]	0.34669	0.51931	0.79121
[1 2 3 5 6 7 8 9 10]	0.36959	0.51103	0.7206	[1 2 3 4 5 6 7 10]	0.36703	0.56138	0.75431
[1 2 3 4 5 6 7 8 9 10]	0.3291	0.50448	0.71698	[2 3 4 5 6 7 8 9 10]	0.35552	0.53069	0.75966
[1 2 3 4 5 6 7 8 9 10]	0.32621	0.50862	0.71448	[1 2 3 4 5 6 7 8 9 10]	0.33131	0.50586	0.7156

Formulation

Minimize the independence between the projected features XW and labels, Y

The parameter controls how sparse the resulting matrix will be, and how many features are selected

$$\min_{W \in \mathbb{R}^{q \times d}} -HSIC\,(XW, Y) + \lambda \sum_{j=1}^{d} \|w_j\|_\infty$$

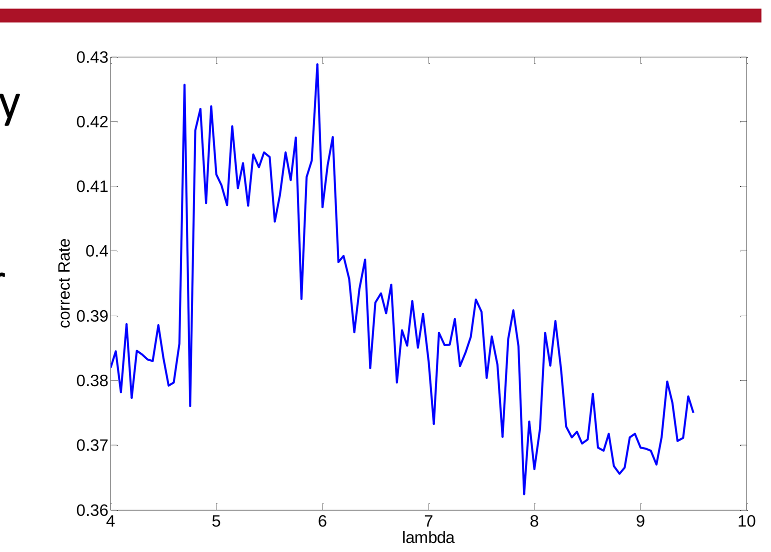
The L_1 -L_∞ norm on the rows of the projection matrix induces row-sparsity

This is solved as a constrained optimization problem

$$\min_{W \in \mathbb{R}^{q \times d}} -HSIC\,(XW, Y)$$
$$s.t. \|w_j\|_\infty \leq \alpha \;\; \forall j \in [1, d]$$

Future Work

- Exploration of column sparsity
- Sensitivity analysis in optimization
- Further analysis of parameter selection



References

Mahdokht Masaeli, Glenn Fung, and JenniferG. Dy. “From Transformation-based Dimensionality Reduction to Feature Felection”. In ICML, pages 751–758, 2010.

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