Ranking Support Matrix Machine for Vehicle Face Prediction

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Introduction

- The chief goal of our system is to predict the most appealing vehicle "face", comprised of the headlights, given the demographic information of an individual.

Consumer Demographics → RSMM → Ranked Set of Recommended Vehicles → Image Processing Decomposition → Predicted Set of Recommended Vehicle Faces

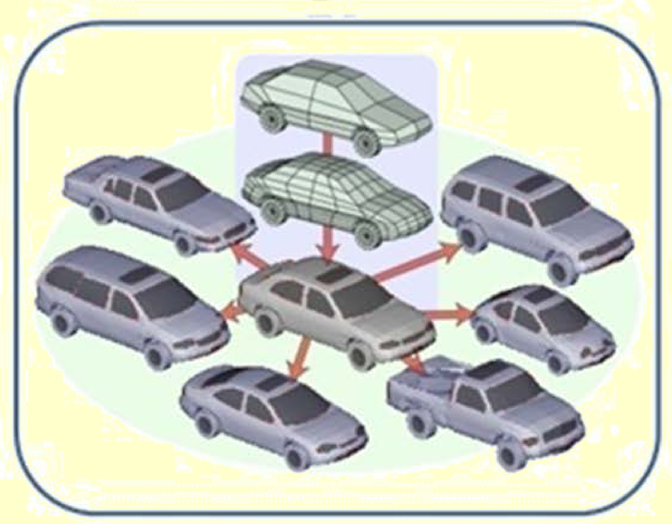
Definitions

B ***V***

x_i = {age, sex, education, ...}

$\overrightarrow{x_{uk}} = \{u_1, u_2 ..., u_n\}$, $\overrightarrow{x_{uk}} \in B$

B: Demographic space



x_c = {headlights}

$\overrightarrow{x_{ci}} = \{c_1, c_2 ..., c_m\}$, $\overrightarrow{x_{ci}} \in V$

V: Feature space

RSMM

Parametric indicator as bilinear function of

$$s_{ki} = \overrightarrow{x_{uk}} W \overrightarrow{x_{ci}}^T = \vec{w}(\overrightarrow{x_{ci}} \otimes \overrightarrow{x_{uk}})$$

Thus, we can define the kronecker product in (1) as the feature function of

$$\Phi_{uk}(\overrightarrow{x_{ci}}) = \overrightarrow{x_{ci}} \otimes \overrightarrow{x_{nk}}$$

We use the hinge loss function for a given $\overrightarrow{x_{uk}}$ if $\overrightarrow{x_{ci}} \succ \overrightarrow{x_{cj}}$

$$\vec{w}^T(\Phi_{uk}(\vec{x}_{ci}) - \Phi_{uk}(\vec{x}_{cj})) > 0$$

Objective function

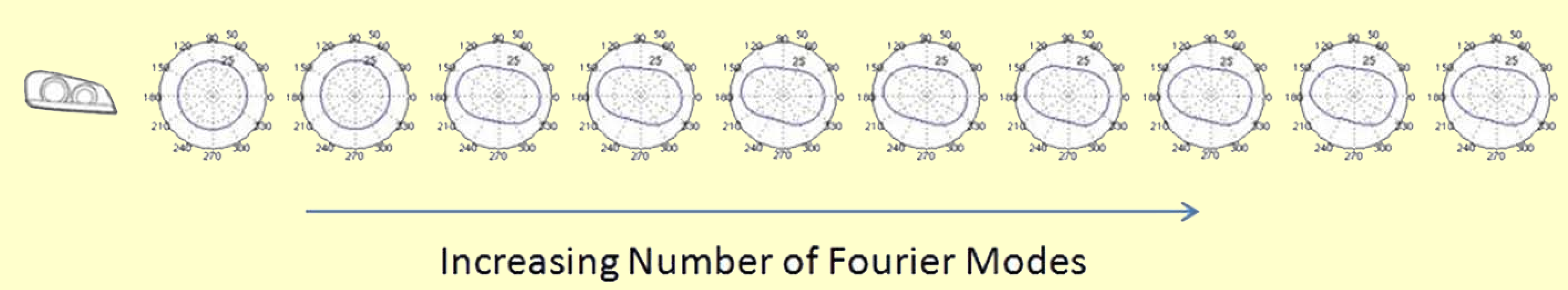
$$min \sum_u \sum_{i,j} [1 - \vec{w}^T(\Phi_{uk}(\vec{x}_{ci}) - \Phi_{uk}(\vec{x}_{cj}))]_+ + \|\vec{w}\|_2^2$$

Feature Extraction

- Comparison of methods:

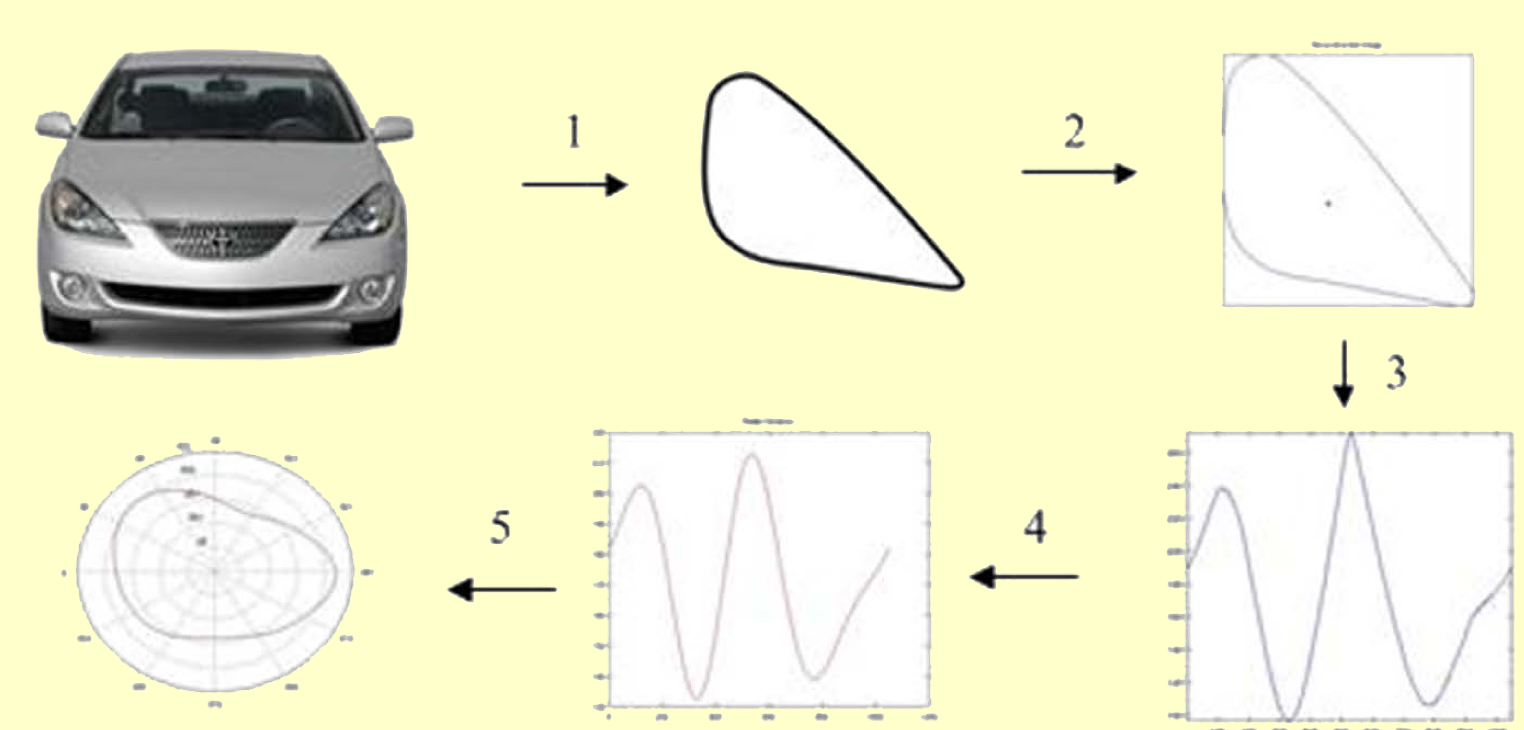
	Size of Encoded Data	Fidelity of Curvature	Robustness to Noise
Image Encoding	High Dimensional (All Pixels)	High Fidelity	High
Shape Descriptors	Low Dimensional (BoundarySize×2)	Low Fidelity	High
Relief Graphs	Low Dimensional (Edge Size×2)	Medium Fidelity	Low

- Fourier Descriptors based on shape:



- ➢ The lower frequency descriptors contain information about the general features of the shape
- ➢ These high frequency descriptors are set to zero

Car Image → 1.Headlight extraction → Headlight → 2.Pre-processing → Contour Image → 3.FFT → Fourier Transform Coefficients → 4.Denoising & Filtering → Fourier Descriptors → 5.Feature Inversion → Reconstructed Contour



Results

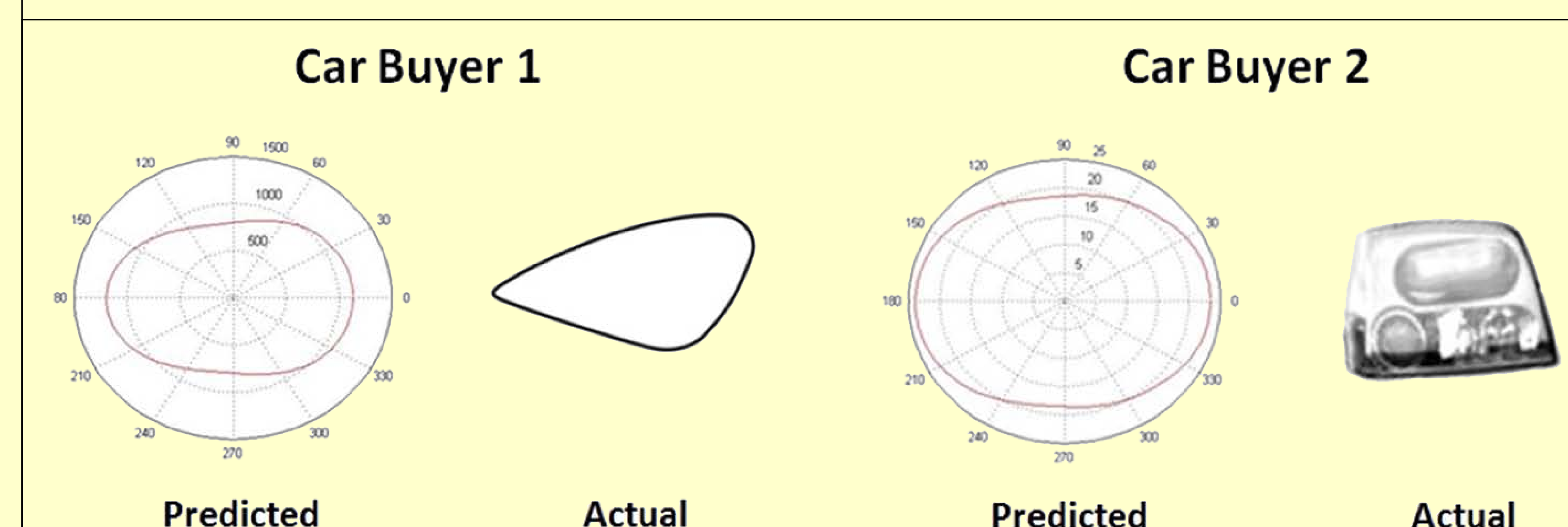
	MovieLens	Our Subset
Range of Ratings	1~5	1~5
Number of Users	6040	800
Number of Items	3706	80

$$NDCG = \frac{DCG}{IDCG} = \frac{\sum_{i=1}^{p} \frac{2^{rel_i} - 1}{\log_2(1+i)}}{\sum_{i=1}^{p} \frac{2^{rel_{i^*}} - 1}{\log_2(1+i)}}$$

Algorithm	Random	Affinity Model	Pairwise Regression	RSMM
NDCG	0.4158	0.4489	0.4972	0.4614

Overall Performance =
0.5 (Rank1) +
0.3(Rank2) +
0.1(Rank3) +
0.05(Rank4) +
0.05Rank(5)

Rank	Car Buyer 1, $\overrightarrow{x_1}$	Car Buyer 2, $\overrightarrow{x_2}$
1	Lexus ES	Volvo S40
2	Lincoln LS	Lexus LS
3	Acura TL	Chevy Impala
4	VW Phaeton	Suzuki Forenza
5	Pontiac GTO	Jaguar F-Type



Extension

Future Algorithmic Improvements
Optimization of $\vec{c}$ provides better regularization on the loss function set.
Nonlinear kernel trained with expert knowledge
Conjugate linear gradient method for deducing $\vec{w}$

Future Algorithm Applications
Recommender Systems:
Combine the merits of Content-Based filter and Collaborative Filtering
Structural Bound rather than Variance Minimization