Model Adaptation for Personalized Opinion Analysis

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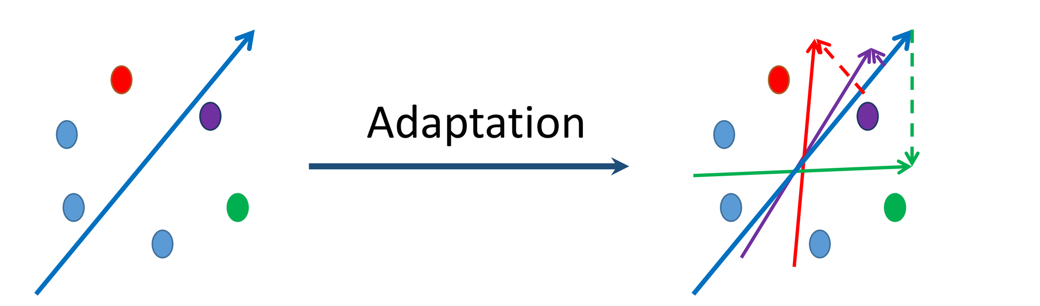
Abstract

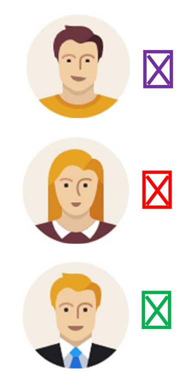
Humans are idiosyncratic and variable: towards the same topic, they might hold different opinions or express the same opinion in various ways. It is hence important to model opinions at the level of individual users; however it is impractical to estimate independent sentiment classification models for each user with limited data. In this work, we adopt a model-based transfer learning solution -- using linear transformations over the parameters of a generic model -- for personalized opinion analysis.

Model Adaptation Framework

- Adapt a linear classifier using linear transformations (shifting, scaling and rotation):



Global Model $f(x) = w^T x$ — Personalized Models $f^u(x) = (A^u \tilde{w}^s)^T x$



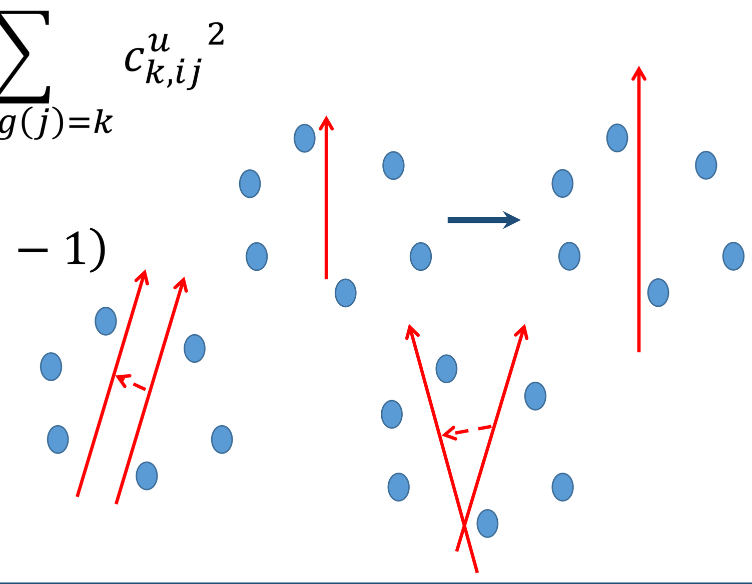
where
$$A^u = \begin{pmatrix} a^u_{g(1)} & c^u_{g(1),12} & 0 & 0 & b^u_{g(1)} \\ c^u_{g(2),21} & a^u_{g(2)} & \cdots & 0 & b^u_{g(2)} \\ 0 & \cdots & \cdots & \ddots & \vdots \\ 0 & 0 & \cdots & a^u_{g(V)} & b^u_{g(V)} \end{pmatrix}$$

- **Objective Function:** $\max_{A^u} L(A^u) = L_{LR}(D^u; P^u) + R(A^u)$

Loss function — Complexity of adaptation: prefer no adaptation

where $$R(A^u) = -\frac{\eta}{2}\sum_{k=1}^{K}(a^u_k - 1)^2 - \frac{\sigma}{2}\sum_{k=1}^{K} {b^u_k}^2 - \frac{\epsilon}{2}\sum_{k=1}^{K}\sum_{i,g(i)=k}\sum_{j\neq i,g(j)=k} {c^u_{k,ij}}^2$$

- **Derivatives:**
  - **Scaling:** $\frac{\partial L(A^u)}{\partial a_k} = \sum_{d=1}^{D^u}\{y_d[1-p(y_d|x_d)]\sum_{i,g(i)=k} w^s_i x_{d_i}\} - \eta(a_k - 1)$
  - **Shifting:** $\frac{\partial L(A^u)}{\partial b_k} = \sum_{d=1}^{D^u}\{y_d[1-p(y_d|x_d)]\sum_{i,g(i)=k} x_{d_i}\} - \sigma b_k$
  - **Rotation:** $\frac{\partial L(A^u)}{\partial c_{k,ij}} = \sum_{d=1}^{D^u}\{y_d[1-p(y_d|x_d)]w^s_j x_{d_i}\} - \epsilon c_{k,ij}$



Dataset and Preprocessing

- **Data source:** Amazon review data from Stanford SNAP website.
- **Preprocessing:**
  - Remove users who have more than 1000 and those who have more than 90% positive or negative reviews.
  - Ratings greater than 3 stars are labeled as Positive others are Negative.
- **Features design:**
  - Bag-of-words review document representation.
  - Unigram and bigram TF-IDF features.
  - Chi-square and information gain for feature selection; 5,000 text features for final vocabulary.

Baselines

- **Instance-based adaptation:**
  - Select k-nearest neighbors of each testing review.
  - Estimate classifier using the expanded dataset.
- **Model-based adaptation:** enforces the adapted model to be close to the global model via additional L2 regularization.

Results & Insights

1- Online adaptation:
- 10,000 testing users: 65% Light ([2-10] reviews),35% Medium ([11-50] reviews),and 0,1% Heavy ([51-200] reviews).
- For each testing review, we test up-to-date model, evaluate against ground-truth label, and use feedback to adapt model.

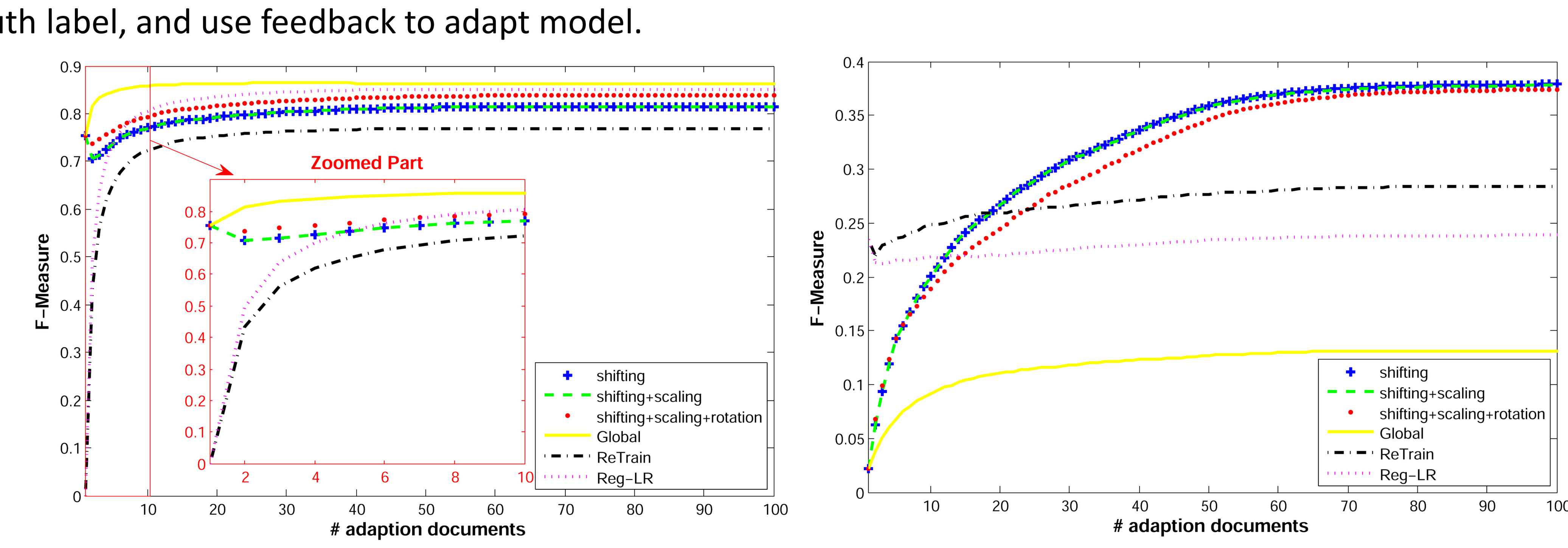


Figure 1: Online adaptation performance comparaisons.

2- Feature Grouping:
- *Cross* is the best; Random is the worse.
- k = 400 provided best positive/ negative balance.

Table 1: Effect of feature grouping in LinAdapt.

Method	Metric	100	200	400	800
Rand	Pos F1	0.691	0.692	0.696	0.686
	Neg F1	0.295	0.298	0.300	0.322
SVD	Pos F1	0.691	0.698	0.704	0.697
	Neg F1	0.298	0.302	0.300	0.322
Cross	Pos F1	0.701	0.702	0.705	0.700
	Neg F1	0.298	0.299	0.303	0.328

3- Performance gain:
- Decompose classification performance by user class.
- Compare the performance against the global model.
- LinAdapt outperform all models in negative class.

Table 2: User-level performance gain over global model from ReTrain, Reg-LR and LinAdapt.

Method	User Class	Pos F1	Neg F1
ReTrain	Heavy	-0.092	0.155*
	Medium	-0.095	0.235*
	Light	-0.157*	0.255*
Reg-LR	Heavy	-0.010	0.109*
	Medium	-0.005	0.206*
	Light	-0.060	0.232*
LinAdapt	Heavy	-0.046	0.248*
	Medium	-0.049	0.235*
	Light	-0.091	0.117*

* p-value<0.05 with paired t-test.

4- Transformed features analysis:
- We computed the variance of the absolute difference between the feature weights in adapted models and global model.
- We analyzed the variance range across users against the weight from the global model.

Table 3: Top 10 words with the highest and lowest variance of learned polarity in LinAdapt.

Variance	Features		
Highest	waste	good	attempt
	money	save	return
	poor	worst	annoy
Lowest	lover	correct	poor
	care	the product	odd
	sex	evil	less than

Table 4: Learned sentiment polarity range of five typical words in LinAdapt.

Feature	Range	Global Weight	Used as Positive	Used as Negative
experience	[-0.231,0.232]	0.002	3348	1503
good	[-0.170,0.816]	0.032	8438	1088
waste	[-0.445,0.069]	-0.019	384	6500
annoy	[-0.630,0.144]	-0.006	1490	5662
money	[-0.439,0.074]	-0.013	646	6238

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