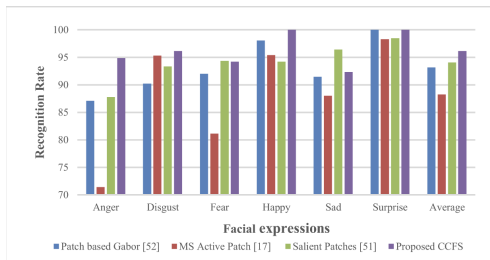
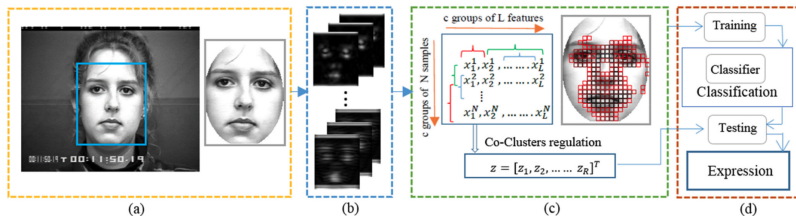


Co-Clustering to Reveal Salient Facial Features for Expression Recognition

- ▶ **Proposal** Use co-clustering to select features that can be used to classify facial expressions
- ▶ **Idea**
 - ▶ Use Gabor filter to extract features vectors from facial images
 - ▶ Use co-cluster to build a relationship chain
Class $\overset{\text{label}}{\sim}$ Samples $\overset{\text{co-cluster}}{\sim}$ Features
- ▶ **Method**
 - ▶ Use Gabor filter to extract features from facial images
 - ▶ Use co-clustering to attain a subset of features and samples
 - ▶ Find the probability that a co-cluster is related to a certain class
 - ▶ Features with high probability are selected

Co-Clustering to Reveal Salient Facial Features for Expression Recognition



My Proposal

- ▶ **Proposal:** Use co-cluster to select features in NLP
- ▶ **Aims:** Use fewer features to get good prediction results, reducing the time and computational overhead of NLP training.
- ▶ **Method:**
 - ▶ Word-embedding or n -gram to extract features from text
 - ▶ (Maybe) Generate more features from the results above
 - ▶ Use co-clustering to attain a subset of features and samples
 - ▶ Select features that are related to a certain class most

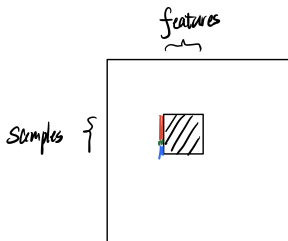


Figure: My Proposal, colors for classes

Understanding Black-box Predictions via Influence Functions (ICML 2017 Best Paper)

- ▶ **Proposal:** Influence function measures the impact of training data on the model - selection features
- ▶ **Method:**
 - ▶ Influence function of samples on model parameters: Formula 1
 - ▶ The influence function of samples on loss: Formula 2
 - ▶ The influence function of samples on the selection of features: formula 3
- ▶ **Discussion:** Different methods (co-cluster & influence function) for the same aims, need performance comparison

Method:

- ▶ Influence function of samples on model parameters:
Formula 1
- ▶ The influence function of samples on loss: Formula 2
- ▶ The influence function of samples on the selection of features: formula 3

$$z_\delta \stackrel{\text{def}}{=} (x + \delta, y), \quad \hat{\theta}_{\epsilon, z} \stackrel{\text{def}}{=} \arg \min_{\theta \in \Theta} \frac{1}{n} \sum_{i=1}^n L(z_i, \theta) + \epsilon L(z, \theta)$$

$$\hat{\theta}_{\epsilon, z_\delta, -z} \stackrel{\text{def}}{=} \arg \min_{\theta \in \Theta} \frac{1}{n} \sum_{i=1}^n L(z_i, \theta) + \epsilon L(z_\delta, \theta) - \epsilon L(z, \theta)$$

$$\mathcal{I}_{\text{up, params}}(z) \stackrel{\text{def}}{=} \frac{d\hat{\theta}_{\epsilon, z}}{d\epsilon} \Big|_{\epsilon=0} = -H_{\hat{\theta}}^{-1} \nabla_{\theta} L(z, \hat{\theta})$$

$$\begin{aligned} \mathcal{I}_{\text{pert, loss}}(z, z_{\text{test}})^{\top} &\stackrel{\text{def}}{=} \nabla_{\delta} L(z_{\text{test}}, \hat{\theta}_{z_\delta, -z})^{\top} \Big|_{\delta=0} \\ &= -\nabla_{\theta} L(z_{\text{test}}, \hat{\theta})^{\top} H_{\hat{\theta}}^{-1} \nabla_x \nabla_{\theta} L(z, \hat{\theta}) \end{aligned}$$