Multi-class Multi-annotator Active Learning with Robust Gaussian Process for Visual Recognition

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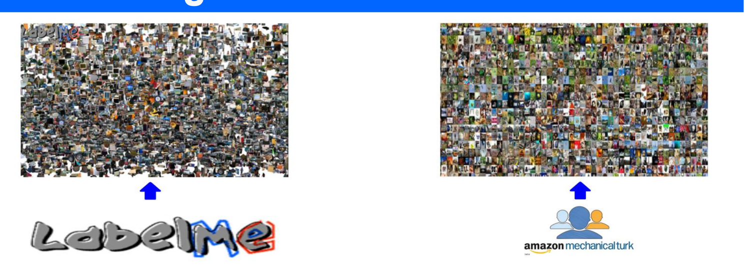
Background and motivation



Crowd-sourced labeling

- Pros: cheap and fast to obtain large-scale labeled data.
- Cons:
  1). Noisy labels.
  2). Difficulties in label quality control.
  3). No mechanism to prioritize the data labeling.

Previous work

- Majority voting based confidence. [Donez et al 2009-2010]
- Incremental relabeling mechanism. [Zhao et al 2011]
- Active learning with multiple annotators. [Hua et al 2013, Long et al 2013 & 2015]

Motivation

- Few research work of active learning investigate multi-class scenario, and reducing multi-class into binary cases may degrade the performance.
- Multiple annotator case has not been explored in the multi-class active learning.
- We want to make full use of diverse opinions from the annotators.

Datasets

E-Album (15 peoples, 145 instances, 84.83%-95.17%)
G-Album (13 peoples, 441 instances, 75.06%-98.41%)
ImageNet (3 categories, 7814 images, 91.89%-92.68%)

Comparisons

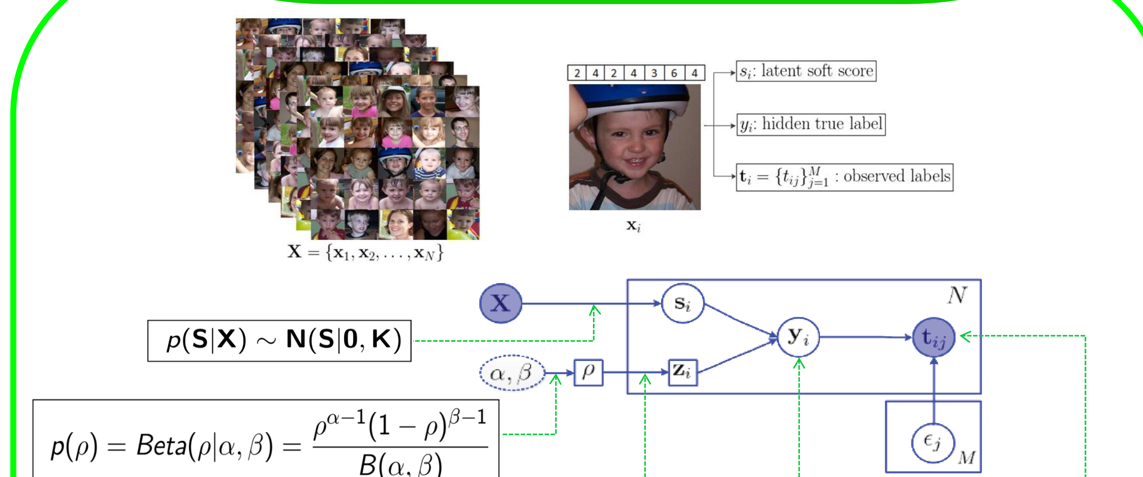
Method	Label treatment	Sample	Annotators
MARMGPC-ASAL	Joint processing	Active	Active
MARMGPC-ASRL	Joint processing	Active	Random
MARMGPC-RSAL	Joint processing	Random	Active
MARMGPC-RSRL	Joint processing	Random	Random
RMGPC-MVAS	Majority voting	Active	-
RMGPC-MVRS	Majority voting	Random	-
RALF-MVAS	Majority voting	Active	-
RALF-MVRS	Majority voting	Random	-

Summary of acronyms:

- RMGPC: Robust Multi-class Gaussian Processes Classifier [Hernandez-Lobato et al. NIPS'11].
- MARMGPC: Multi-Annotator Robust Multi-class Gaussian Processes Classifier (our model) [Long et al. ICCV'15].
- RALF: Reinforced Active Learning Formulation [Ebert et al.,CVPR 12].
- AS/RS: Active/Random selection of samples.
- AA/RA: Active/Random selection of annotators.
- MV: Majority voting.

Sponsors

Graphical model



$p(\mathbf{S}|\mathbf{X}) \sim \mathbf{N}(\mathbf{S}|\mathbf{0}, \mathbf{K})$

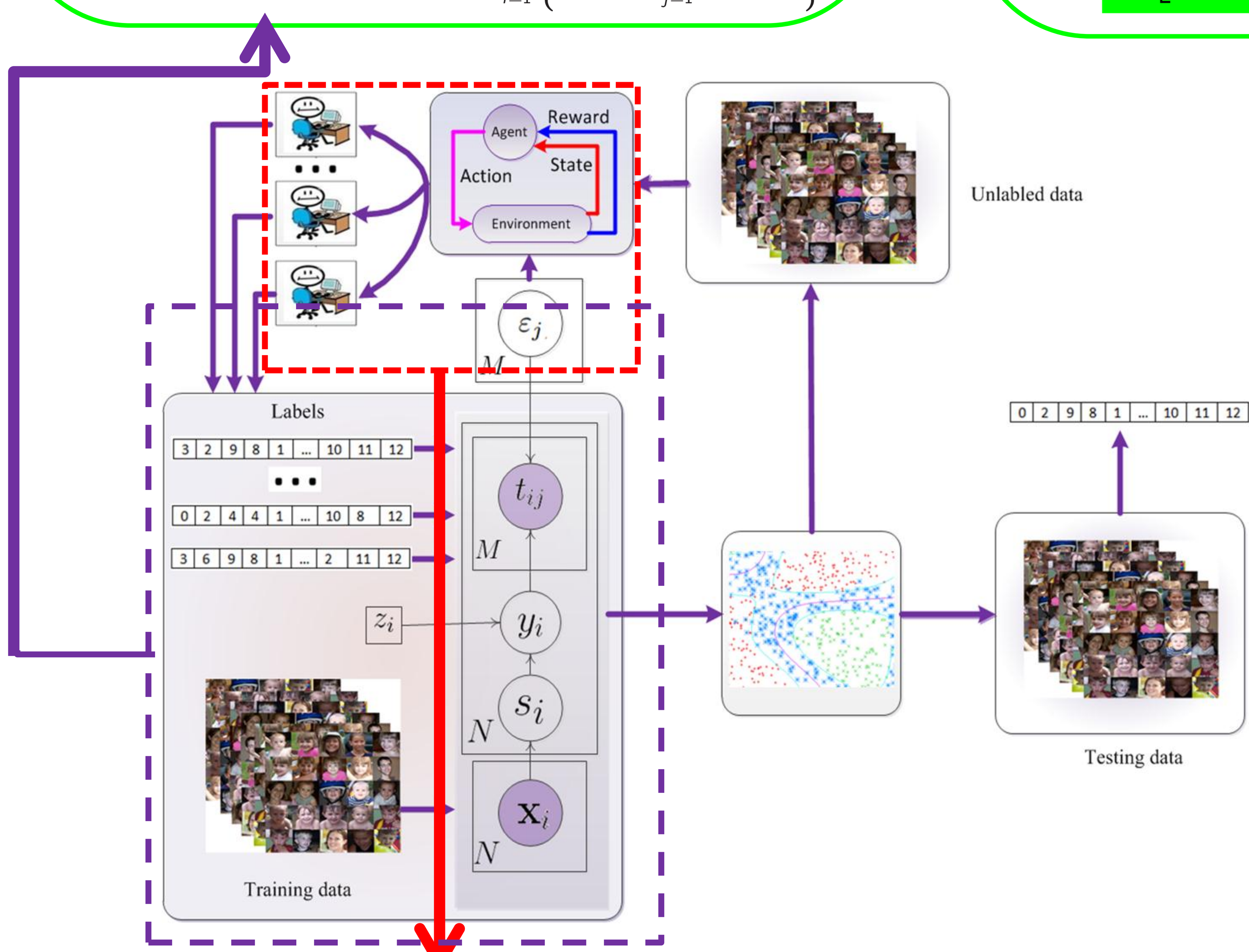
$p(\rho) = Beta(\rho|\alpha, \beta) = \frac{\rho^{\alpha-1}(1-\rho)^{\beta-1}}{B(\alpha, \beta)}$

$p(\mathbf{z}|\rho) = Bern(\mathbf{z}|\rho) = \prod_{i=1}^{N} \rho^{z_i}(1-\rho)^{1-z_i}$

$p(y_i|\mathbf{s}_i, z_i) = \left[\prod_{k \neq y_i} H(s_i^{y_i} - s_i^k)\right]^{1-z_i} \left[\frac{1}{C}\right]^{z_i}$

$p(t_{ij}|y_i, \epsilon_j) = \epsilon_j H(y_i = t_{ij}) + (1-\epsilon_j) H(y_i \neq t_{ij})$

$$p(\mathbf{S}, \mathbf{Y}, \mathbf{T}, \rho, \mathbf{z}|\mathbf{X}, \Theta) \propto p(\mathbf{S}|\mathbf{X})p(\rho)p(\mathbf{z}|\rho) \prod_{i=1}^{N} \left\{ p(y_i|\mathbf{s}_i, z_i) \prod_{j=1}^{M} p(t_{ij}|y_i, \epsilon_j) \right\}$$



Expectation propagation

$$p(y_u|\mathbf{x}_u, \mathbf{D}_L) = \sum_{z_u} \int_{\mathbf{S}} p(y_u|\mathbf{s}_u, z_u)p(z_u|\rho)p(\mathbf{S}|\mathbf{D}_L, \mathbf{x}_u) d\rho d\mathbf{S}$$
$$= \sum_{z_u} \int_{\mathbf{s}_u} p(y_u|\mathbf{s}_u, z_u)p(z_u|\rho) \int_{\mathbf{S}_L} p(\mathbf{S}|\mathbf{D}_L, \mathbf{x}_u) d\rho d\mathbf{S}_L d\mathbf{s}_u$$

where $p(\mathbf{S}|\mathbf{D}_L, \mathbf{x}_u) \propto \left[\prod_{k=1}^{C} \psi_k\right] \psi_\rho \left[\prod_{s_i \in \mathbf{S}_L} \psi_i\right] \left[\prod_{s_i \in \mathbf{S}_L} \psi_{it}\right]$

$$\psi_{it} = p(\mathbf{t}_i|\mathbf{s}_i, z_i, \epsilon) = \sum_{y_i=1}^{C} p(y_i|\mathbf{s}_i, z_i) \prod_{j} p(t_{ij}|y_i, \epsilon_j)$$

We resort to Expectation Propagation [Minka 2001]:

$$\psi_\rho \left[\prod_{s_i \in \mathbf{S}_L} \psi_i\right] \left[\prod_{s_i \in \mathbf{S}_L} \psi_{it}\right] \approx \tilde{\psi}_\rho \left[\prod_{s_i \in \mathbf{S}_L} \tilde{\psi}_i\right] \left[\prod_{s_i \in \mathbf{S}_L} \tilde{\psi}_{it}\right]$$

Inference

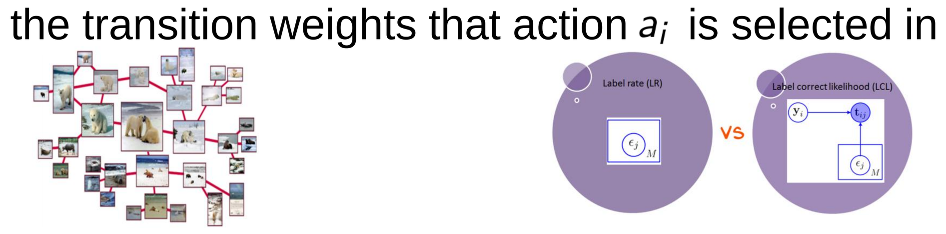
For any data sample $\mathbf{x}_u$,

$$p(y_u|\mathbf{x}_u, \mathbf{D}_L) \approx \frac{\bar{\rho}}{C} + (1-\bar{\rho}) \int \mathcal{N}(s_u|m_u^{y_u}, v_u^{y_u}) \prod_{k \neq y_u} \Phi\left(\frac{s_u - m_u^k}{\sqrt{v_u^k}}\right) ds_u$$

where $\bar{\rho} = \frac{\alpha}{\alpha + \beta}$

Reinforced active learning strategy

The 4-tuple (S, A, R, Q) is defined as follows:
$S = \{U + D + L\}$ with $U \in \{Mar, Ent\}, D \in \{Gra\}$ and $L \in \{LR, LCL\}$.
$A = \{\beta_1, \ldots, \beta_n\} \times S$ with $\beta_i \in [0, 1]$, represents different fixed trade-offs between U and D.
R is the reward for executing action a_i in state s_j.
Q are the transition weights that action a_i is selected in state s_j.



Graph density (Gra) Criterion to select annotators

During active learning process, $a = \max_{a_i} Q(s^{(t-1)}, a_i)$ → optimal β_i + current state $U + D + L$ → take active selection of both samples and top K annotators.

$$Q(s^{(t-1)}, a) \leftarrow Q(s^{(t-1)}, a) + \lambda(r^{(t)} + \gamma(\max_{a_i} Q(s^{(t)}, a_i) - Q(s^{(t-1)}, a))$$

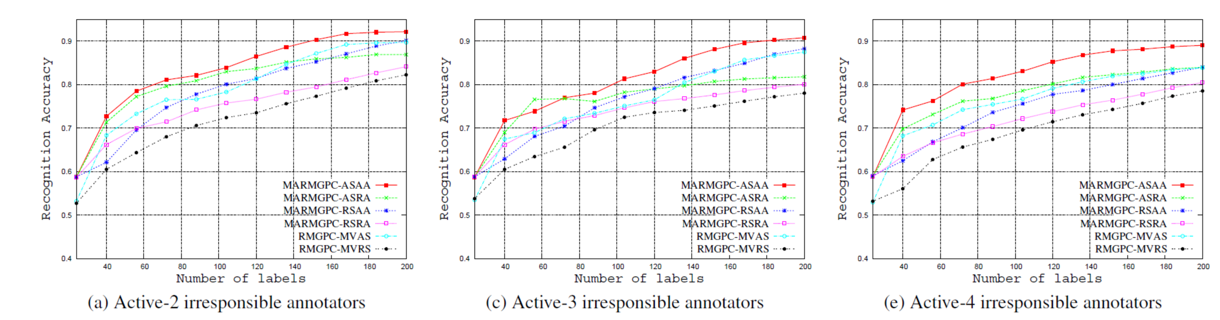
Parameter estimation

$$\log p(\mathbf{T}_L, \mathbf{S}_L|\mathbf{X}_L, \Theta) \geq \sum_{z_i} \int_{\mathbf{S}_L} Q(\mathbf{S}_L) \log \frac{p(\mathbf{z}|\rho)p(\rho)p(\mathbf{T}_L, \mathbf{S}_L|\mathbf{X}_L, \Theta)}{Q(\mathbf{S}_L)}$$
$$= \mathrm{C} + \sum_{z_i} \sum_{i=1}^{L} \int_{\mathbf{s}_i} q(\mathbf{s}_i) \log \{p(z_i|\rho)p(\rho)p(\mathbf{t_i}|\mathbf{s}_i, z_i, \epsilon)\} d\mathbf{s}_i,$$

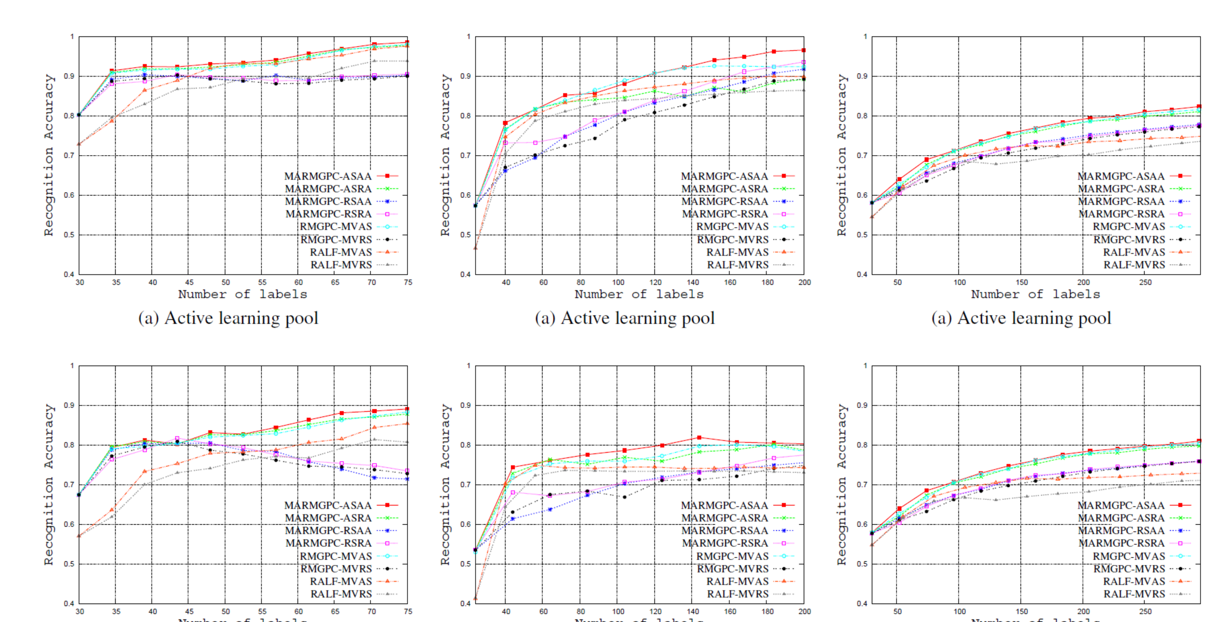
E-Step: Given the current parameter Θ_p, conduct EP inference to obtain and approximate inference of $Q(\mathbf{S}_L)$.
M-Step: Maximize the lower bound of $\log p(\mathbf{T}_L, \mathbf{S}_L|\mathbf{X}_L, \Theta)$ over Θ to obtain a new parameter Θ. $\Theta_p \leftarrow \Theta$.

Simulated experiments

Simulated experiments with 2, 3, 4 irresponsible annotators (with 50% label correctness) on the G-Album.

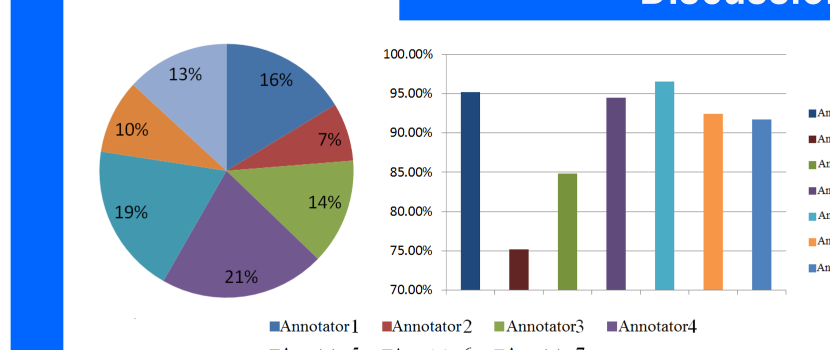


Experiments with real labels

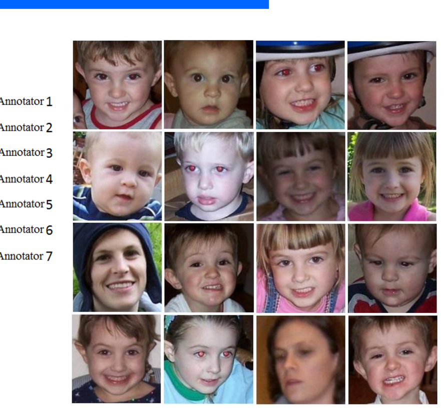


E-Album G-Album ImageNet

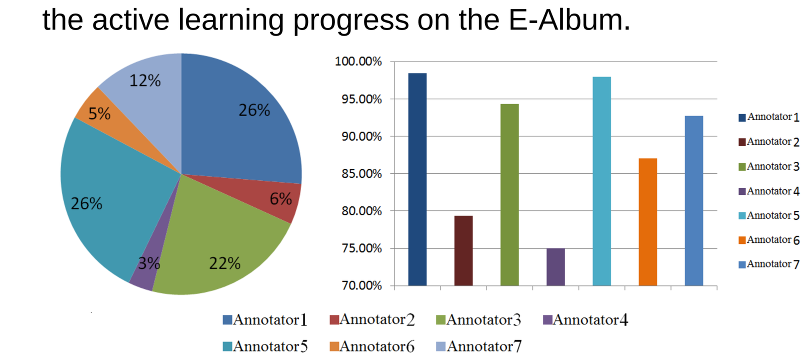
Discussion



The fractions of the used labels from 7 annotators in the active learning progress on the E-Album.



Some examples selected by MARMGPC-ASAA in the early stage on the G-Album.



The fractions of the used labels from 7 annotators in the active learning progress on the G-Album.

	E-Album	G-Album
SVM-MV	70.05%	71.93%
SMGPC-MV	71.64%	73.42%
RMGPC-MV	71.99%	74.30%
RMGPC-GRD	72.29%	75.69%
MARMGPC	72.08%	75.34%

Comparison of recognition performance with different classification model using all the labeled data.

Conclusion

We propose a novel multi-annotator Gaussian process model to deal with multi-class visual recognition. A generalized EM-EP algorithm is derived to estimate the parameters and approximate Bayesian inference. We achieve the adaptive trade-off between exploitation and exploration with reinforcement learning. Our future works includes further developing our proposed MLRMGPC model to make it more efficient and scalable.