Introduction to Active Learning

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- Inefficient! This is where Active Learning comes in.

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  - A1: Embedding if $\theta_i \prec \theta_j$ then $\|\theta_i - r\| < \|\theta_j - r\|$.
  - A2: Consistency Every pairwise comparison is consistent with the global ranking.

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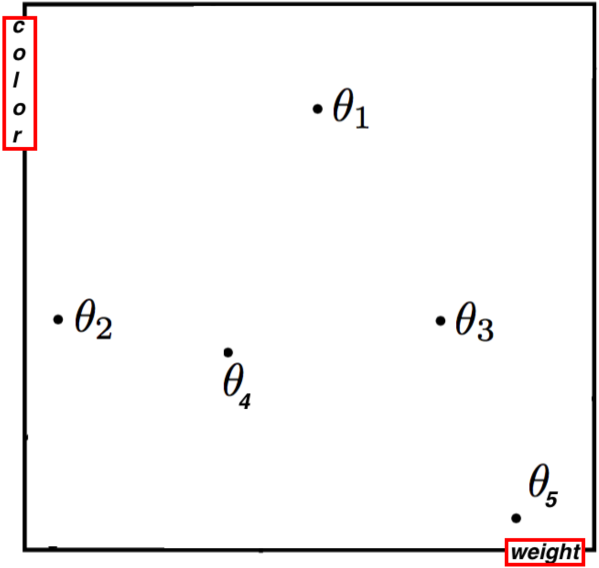

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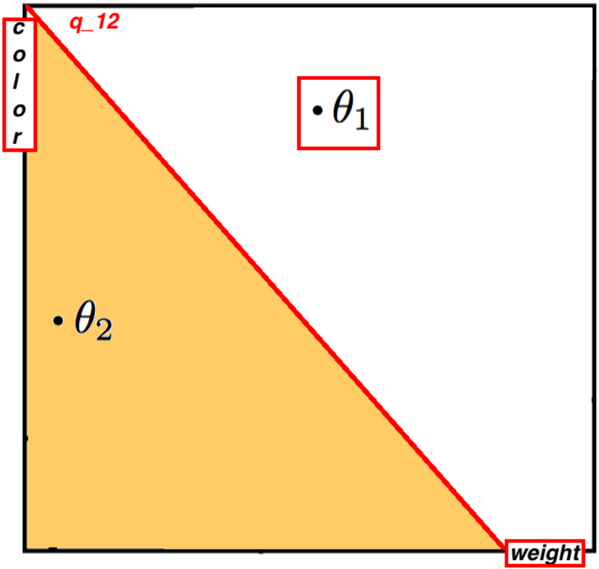

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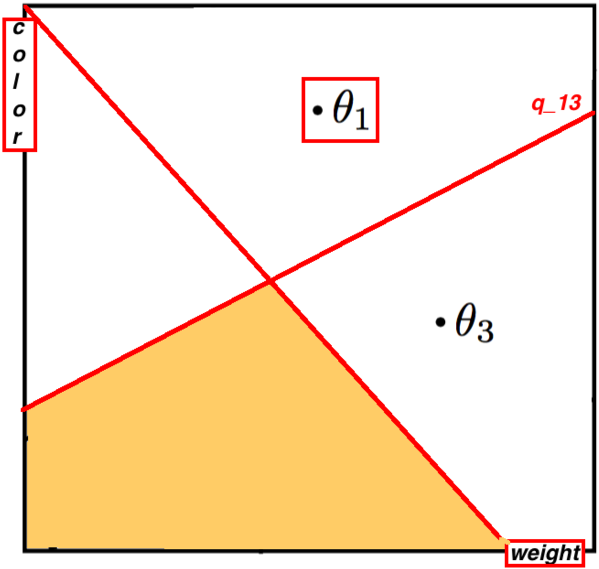

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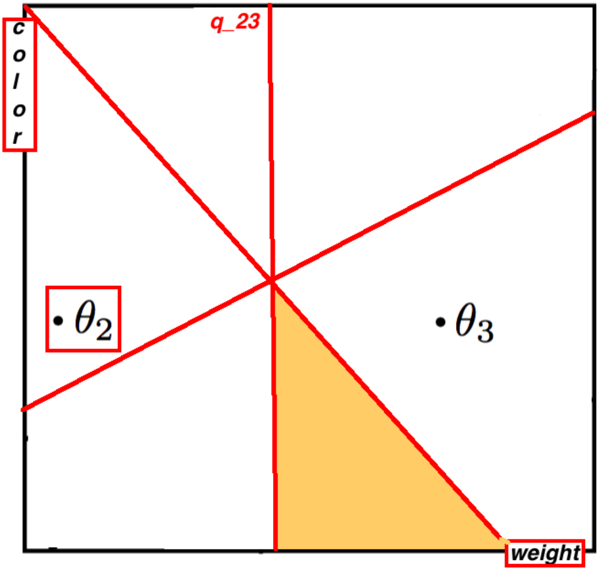

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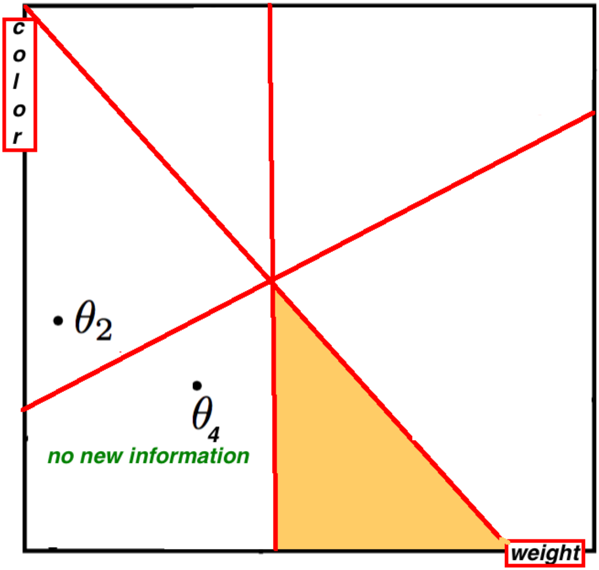

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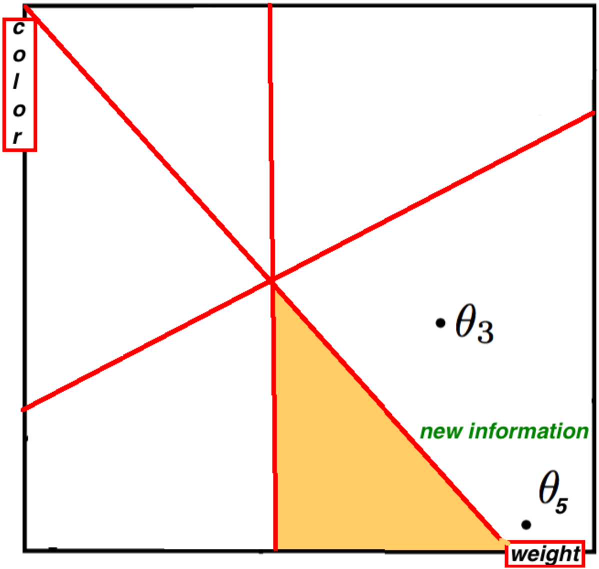

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- Currently using random pairwise queries.
- Opportunity for active learning algorithms.

Thanks!