FACULTAD DE INGENIERÍA Y CIENCIAS

UNIVERSIDAD ADOLFO IBÁÑEZ

A Stacked Generalization Ensemble Model for Help Desk Ticket Assignment

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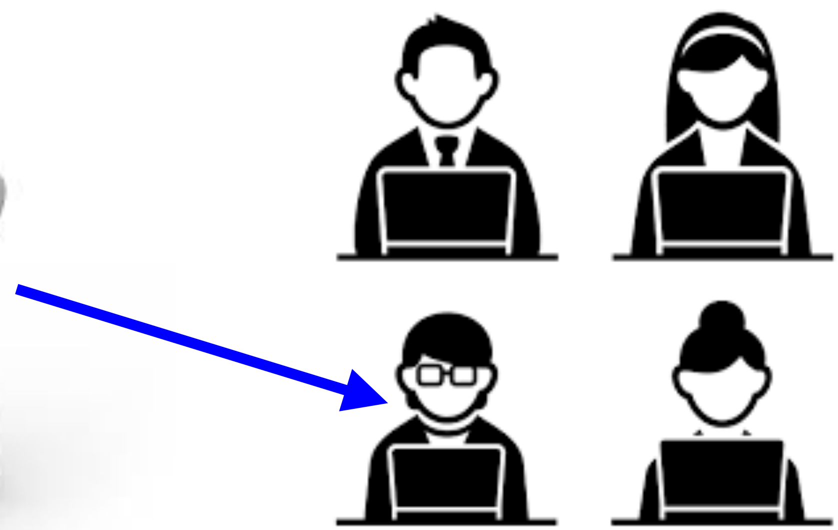
- More than 30 conference papers (KDD, ICDM, WWW) and WOS journals.
- Program committee in more than 40 conference including NeurIPS, KDD, WWW, ICDM, and SCCC.
- Research interest: Machine learning, neural networks, relational learning, statistical network analysis.

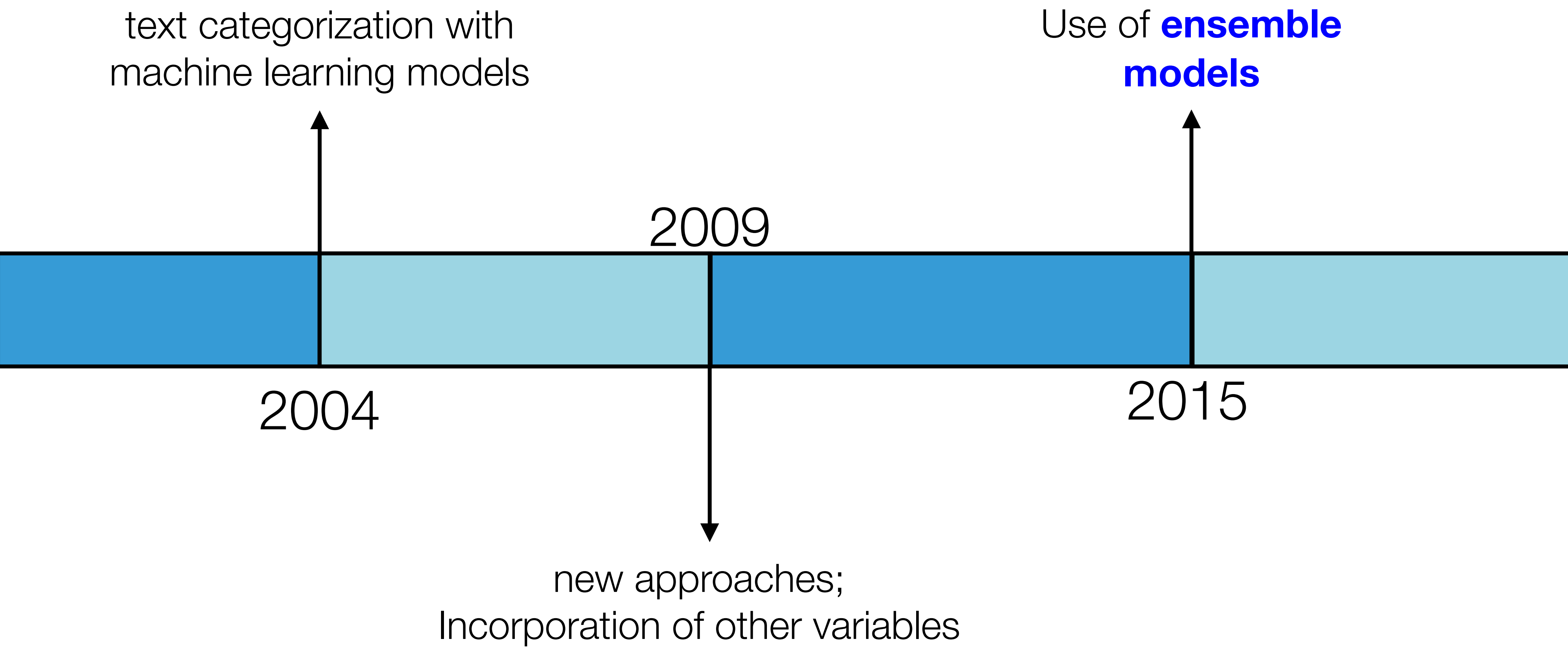
Problem definition

- Technological advances allow automating processes that previously required the direct intervention of a technician in case of an incident.
- In software projects, the bugs (errors in the code) must be analyzed and assigned to an expert for their resolution.
- Large software projects can have 50-60 bugs per day. If each bug is assigned manually in 5 minutes => 3.3 to 5.0 hours dedicated in the assignment task.
- **How can we assign the tickets automatically?**



State of the art

- Current work assumes that most of the data has several variables and text.

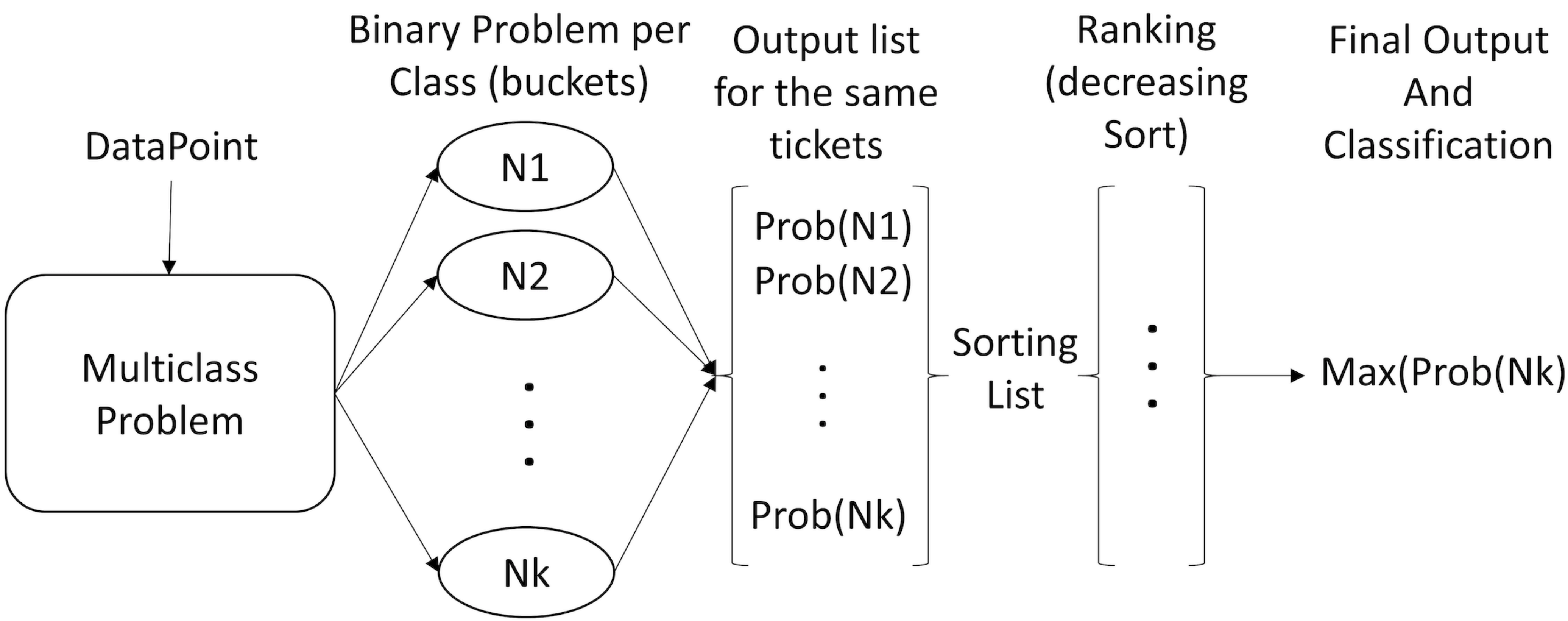


Dataset

- Originally, we had 3,726 tickets between 2016 and 2017:
  - 12 attributes
  - 10 programmers
  - No text data was available
- After cleaning and generation process, we had 1,051 tickets with 14 variables:
  - Origin: nominal (16 values => hospitals)
  - Module: nominal (14 values => category of the ticket)
  - Deadline: binary (1 for ticket with time limit)
  - Occupation: (numerical, 10 variables with the number of tickets that each programmer is currently working)
  - Class: nominal (10 values => programmers)

One Versus Rest (OVR) “ensemble model”

- The One Versus Rest (OVR) approach uses ensembles for k classes:
    - The data is repeated k times, and k models are learned (one per class).
    - Given a data point, k predictions are applied (one per model).
    - The final prediction corresponds to the class with highest probability.



One Versus Rest (OVR) “ensemble model”

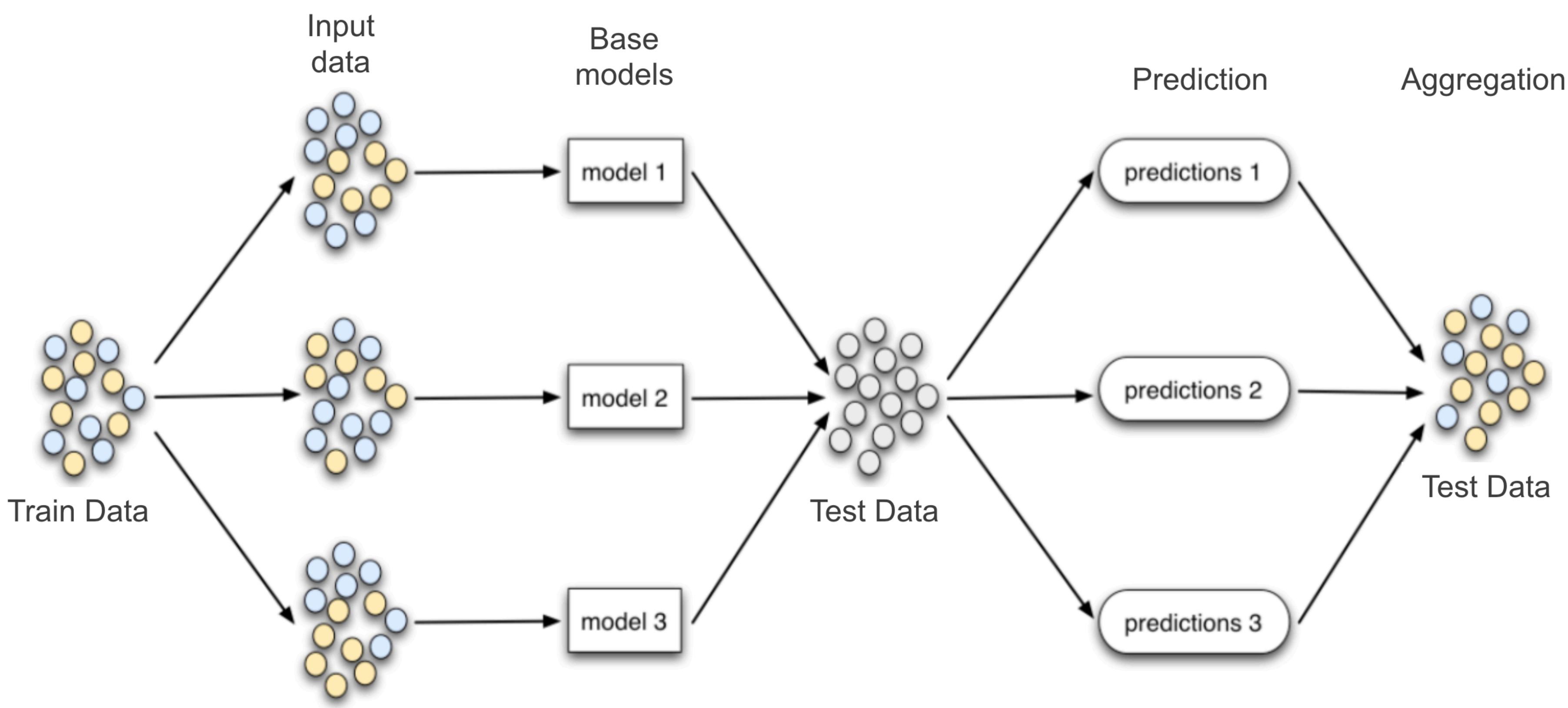
- The One Versus Rest (OVR) approach uses ensembles for k classes:
  - The data is repeated k times, and k models are learned (one per class).
  - Given a data point, k predictions are applied (one per model).
  - The final prediction corresponds to the class with highest probability.
- Example, probabilities for a datapoint, from a dataset with 5 classes.

	class 1	class 2	class 3	class 4	class 5
Ensemble	0.93	0.96	0.45	0.04	0.30

- **Class 2 is selected, the class with highest probability.**

Ensemble models for multiclass prediction

- Typical approach for multiclass problems using ensembles for k classes:
  - The data is repeated m times, and m multiclass-models are learned.
  - Given a data point, m*k predictions are applied (k predictions per model).
  - The final prediction corresponds to an aggregation of the values.



Ensemble models for multiclass prediction

- Example, probabilities using 4 models, from a dataset with 5 classes.

	class 1	class 2	class 3	class 4	class 5
Multiclass 1	0.31	0.32	0.25	0.02	0.10
Multiclass 2	0.44	0.45	0.01	0.02	0.08
Multiclass 3	0.40	0.09	0.05	0.38	0.08
Multiclass 4	0.01	0.03	0.02	0.02	0.92

What class should we predict?

Class 1 is high in 3 models, and wins in one.

Class 2 wins in 2 models.

Classes 3 and 4 should not be selected.

Class 5 has the highest probability of all.

Ensemble models for multiclass prediction

- Ensemble of multiclass models could produce a high diversity in their answer.

	class 1	class 2	class 3	class 4	class 5
Multiclass 1	0.31	0.32	0.25	0.02	0.10
Multiclass 2	0.44	0.45	0.01	0.02	0.08
Multiclass 3	0.40	0.09	0.05	0.38	0.08
Multiclass 4	0.01	0.03	0.02	0.02	0.92

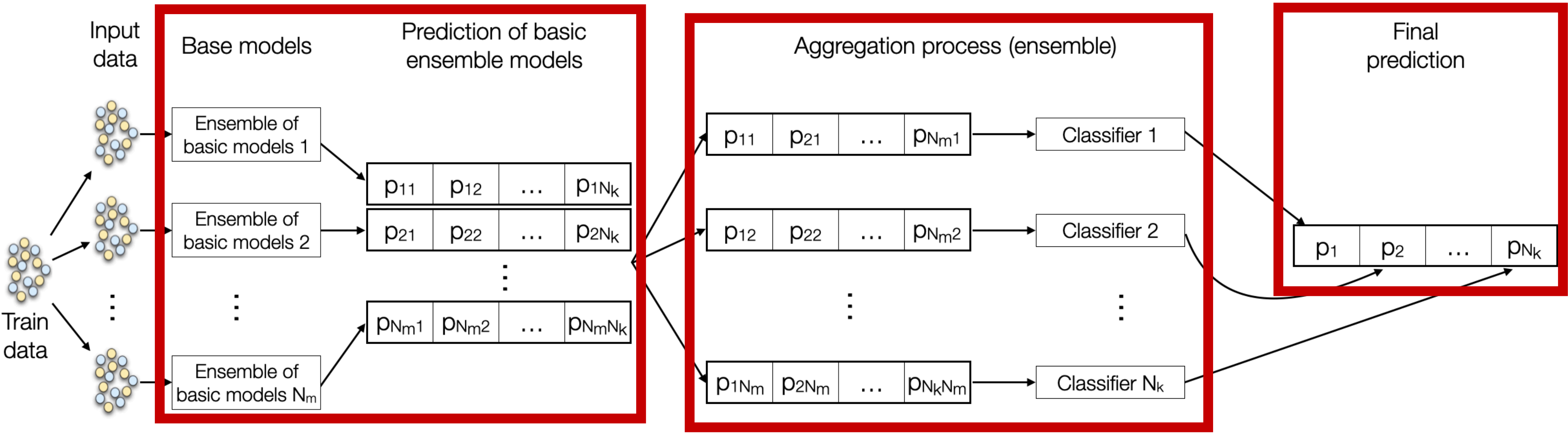
- One versus rest approach give us less information.

	class 1	class 2	class 3	class 4	class 5
Ensemble	0.93	0.96	0.45	0.04	0.30

How can we combine these approaches?

Stacked generalization basic ensemble models

- We propose a stacked generalization process with two levels (the first and second levels are ensemble models instead of basic models).
- We change the basic models for ensemble models (obtaining k probabilities).
- New classifier learns to trust the prediction of the ensembles.
- The final prediction corresponds to the class with highest probability.



Stacked generalization basic ensemble models, example

- Example, probabilities using 4 models, with a dataset with 5 classes.
- Each ensemble learned a probability for each class.

	class 1	class 2	class 3	class 4	class 5
Ensemble 1	0.93	0.96	0.45	0.04	0.30
Ensemble 2	0.94	0.97	0.01	0.02	0.20
Ensemble 3	0.98	0.12	0.05	0.89	0.22
Ensemble 4	0.01	0.03	0.02	0.02	0.92

Stacked generalization basic ensemble models, example

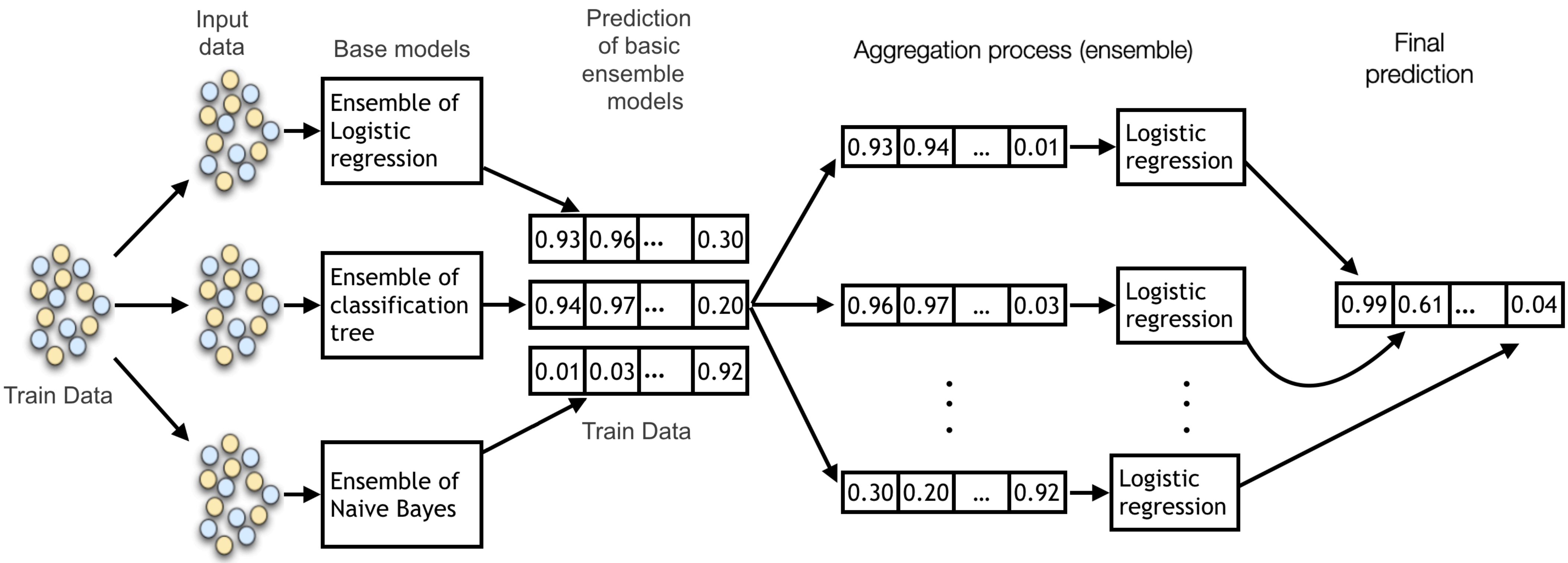
- We generate a “new dataset” based on the predictions.

- We use another ensemble model for the aggregation step, i.e., a new model learns to make the final prediction based on probabilities.

	Ens M.	Ens M. 2	Ens M. 3	Ens M. 4	Est Prob.
class 1	0.93	0.94	0.98	0.01	**0.99**
class 2	0.96	0.97	0.12	0.03	0.61
class 3	0.45	0.01	0.05	0.02	0.20
class 4	0.04	0.02	0.89	0.02	0.05
class 5	0.30	0.20	0.22	0.92	0.04

Stacked generalization basic ensemble models (SGBEM), final model

- For this paper, we use 3 ensembles (Logistic regression, classification tree, and Naive Bayes), and logistic regression for the aggregation process.



Methodology

- We compare SGBEM, our proposed ensemble, against:
  - Random baselines.
  - Multilabel version of basic individual models (KNN, Classification Tree, Logistic Regression, Naive Bayes, SVM).
  - One vs. rest ensemble versions of these basic models.
  - basic Stacked Generalization.
  - Random Forest (random selection of the variables).
  - “Facebook”, an ensemble to predict clicks.
  - XGBoost.

Results, accuracy

- 50 repetitions (70% training and **30% test**).
- Random models perform very bad (complex problem).
- Low and similar performance for basic models.
- Ensembles perform similar to basic models.
- SGBEM obtains, in average, the highest accuracy, and it is statistically significant.

TABLE IV: Accuracy for all models.

Model	Top 1	Top 2	Top 3
SGBEM	**67.0% ± 2.6%**	**80.6% ± 2.5%**	**86.7% ± 1.7%**
Random			
Simple	9.6% ± 1.5%	19.6% ± 2.4%	29.9% ± 2.7%
Weights	28.1% ± 2.5%	43.5% ± 3.0%	53.8% ± 3.2%
KNN	60.0% ± 2.2%	72.2% ± 1.7%	80.2% ± 1.9%
MLR	55.8% ± 2.4%	73.9% ± 2.2%	84.7% ± 1.7%
CT	58.2% ± 2.2%	71.7% ± 2.5%	81.6% ± 2.2%
NB	49.9% ± 2.1%	69.7% ± 2.6%	81.6% ± 2.4%
MLR-NN	56.2% ± 2.4%	70.3% ± 2.0%	80.3% ± 2.0%
SVM	55.4% ± 2.1%	72.0% ± 2.1%	81.4% ± 2.0%
Ensemble			
KNN	54.5% ± 2.3%	68.9% ± 2.2%	78.9% ±2.0%
LR	57.5% ± 2.1%	71.7% ± 2.2%	82.3% ± 1.9%
CT	56.9% ± 2.2%	68.2% ± 2.4%	77.0% ± 2.6%
NB	56.2% ± 2.1%	72.0% ± 2.2%	82.2% ± 1.8%
MLR	56.3% ± 2.3%	70.6% ± 2.4%	80.8% ± 2.2%
SVM	54.7% ± 2.9%	66.5% ± 3.0%	77.1% ± 2.8%
bSG	47.7% ± 15.7%	68.6% ± 10.9%	78.1% ± 13.0%
RF	59.0% ± 2.2%	74.7% ± 2.4%	85.2% ± 2.0%
Facebook	54.6% ± 3.4%	58.0% ± 3.3%	62.4% ± 3.8%
XGBoost	58.5% ± 2.4%	74.6% ± 1.9%	84.9% ± 1.6%

Results, macro F1-score

- 50 repetitions (70% training and **30% test**).
- Similar behaviors than previous results.
- Classification tree and multiclass logistic regression models obtain good performance (but not in all cases)
- SGBEM obtains, in average, the highest macro F1-score, and it is statistically significant.

TABLE V: F1 score for all models.

Model	Top 1	Top 2	Top 3
SGBEM	**52.2%** $\pm$ **4.1%**	**68.1%** $\pm$ **4.4%**	**77.7%** $\pm$ **3.8%**
Random			
Simple	9.8% $\pm$ 1.5%	18.0% $\pm$ 2.4%	26.4% $\pm$ 2.7%
Weights	26.2% $\pm$ 2.7%	36.2% $\pm$ 2.7%	44.1% $\pm$ 3.3%
KNN	49.2% $\pm$ 3.3%	61.5% $\pm$ 2.9%	73.6% $\pm$ 3.1%
MLR	44.6% $\pm$ 3.9%	63.6% $\pm$ 3.3%	**76.2%** $\pm$ **2.7%**
CT	**53.1%** $\pm$ **3.6%**	62.6% $\pm$ 4.5%	73.5% $\pm$ 4.0%
NB	40.2% $\pm$ 3.3%	58.9% $\pm$ 3.2%	73.4% $\pm$ 3.6%
MLR-NN	39.6% $\pm$ 2.7%	58.0% $\pm$ 3.6%	72.4% $\pm$ 2.7%
SVM	36.4% $\pm$ 2.2%	54.9% $\pm$ 2.9%	71.9% $\pm$ 3.5%
Ensemble			
KNN	44.7% $\pm$ 4.0%	56.1% $\pm$ 3.1%	69.0% $\pm$ 3.4%
LR	45.7% $\pm$ 3.0%	59.3% $\pm$ 2.9%	73.3% $\pm$ 2.9%
CT	49.5% $\pm$ 3.3%	60.8% $\pm$ 4.0%	67.7% $\pm$ 4.0%
NB	45.0% $\pm$ 2.9%	60.0% $\pm$ 3.1%	73.9% $\pm$ 2.6%
MLR	38.8% $\pm$ 2.2%	56.8% $\pm$ 3.8%	71.4% $\pm$ 3.4%
SVM	37.0% $\pm$ 2.3%	49.1% $\pm$ 3.1%	64.0% $\pm$ 3.9%
bSG	27.6% $\pm$ 8.7%	61.2% $\pm$ 12.6%	74.9% $\pm$ 8.9%
RF	44.4% $\pm$ 2.7%	62.1% $\pm$ 2.9%	75.6% $\pm$ 3.3%
Facebook	45.6% $\pm$ 3.4%	48.7% $\pm$ 3.1%	53.1% $\pm$ 3.6%
XGBoost	46.2% $\pm$ 3.2%	64.7% $\pm$ 3.0%	**77.1%** $\pm$ **3.0%**

Conclusions

- We presented a new ensemble model (SGBEM) to replicate the assignment of tickets (including bugs) to programmers for help desk support in a software.
- Our approach used a stacked generalization process with two levels
    - The 1st level uses ensemble of models (CT, LT, and NB)
    - The 2nd level (aggregation step) uses a logistic regression.
- We compared our proposed model against 18 baselines including basic individual multiclass classifiers and ensemble models.
- Results showed a statistically significant improvement in 105 of the 108 cases.
- The improvement could be explained by the low variability obtained by the vectors generated in the ensemble used as basic models.

Questions?

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