Context Change and Versatile Models in Machine Learning

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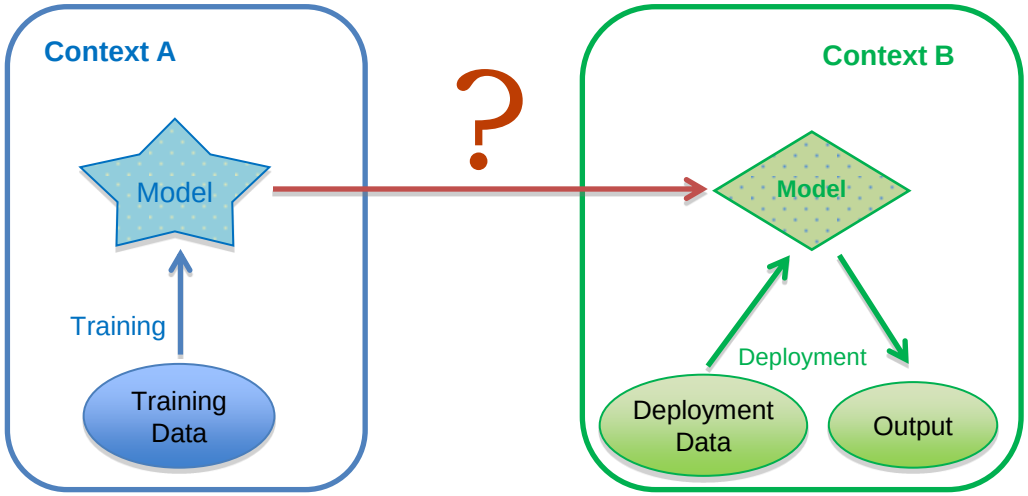
Spot the difference

Outline

- Context change: occasional or systematic?
- Contexts: types and represenation
- Adaptation procedures
- Versatile models
- Kinds of reframing
- Evaluation with context changes
- Related areas
- Conclusions

Context change: occasional or systematic?

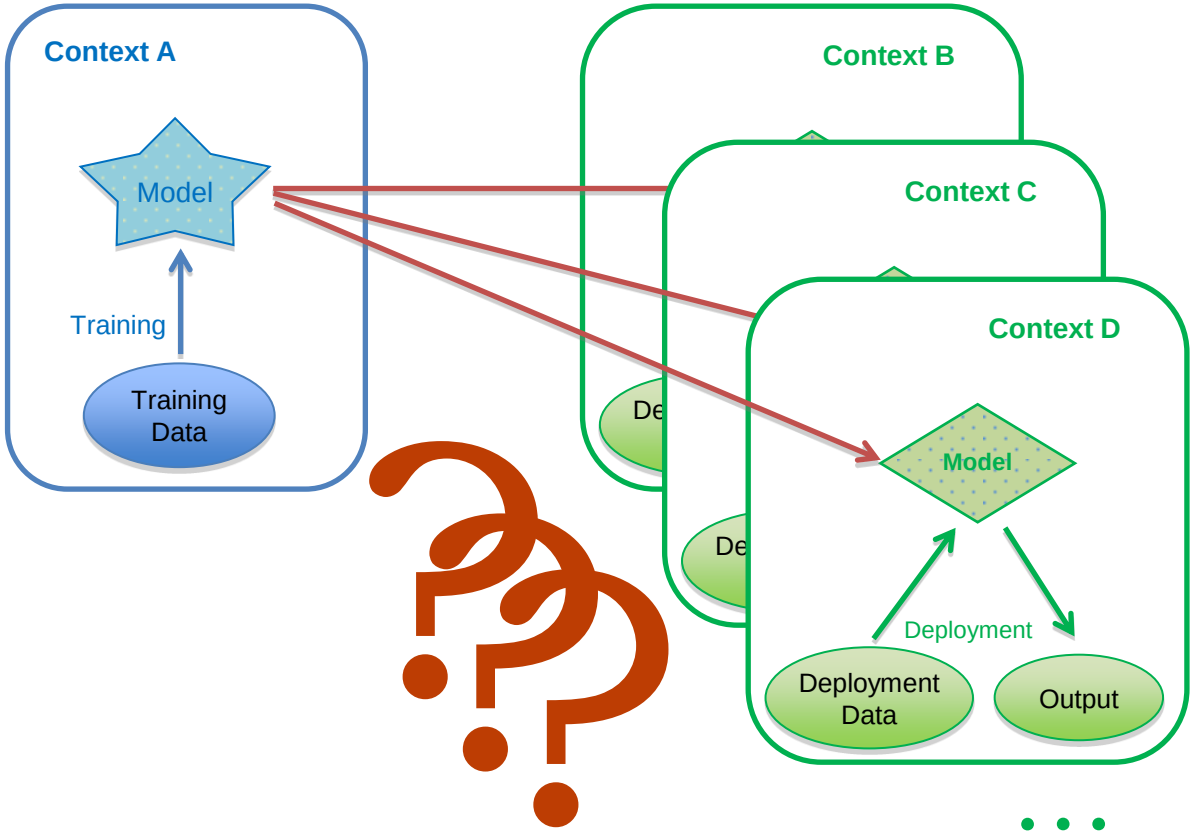
- Contexts (domains, data, tasks, etc.) change.



  - Has the model been prepared to be adapted to other contexts?
  - Did we sufficiently generalise from context A?
  - Is the adaptation process ad-hoc?
  - Should we throw the model away and learn a new one?

Context change: occasional or systematic?

- Contexts change *repeatedly*...



Context change: occasional or systematic?

- How can treat context change in a more systematic way?
  1. Determine which *kinds* of contexts we will deal with.
  2. Describe and *parameterise* the context space.
  3. Use *versatile* models that are better prepared for changes.
  4. Define appropriate *adaptation procedures* to deal with the changes.
  5. Overhaul *evaluation tools* for a range of contexts.

Context change: occasional or systematic?

- Example of an area that does this: ROC analysis
  1. The *kinds* of contexts dealt with are known as 'operating conditions'.
  2. Contexts are *parameterised* as skews (class and cost proportions).
  3. Ranking models provide more *versatility* than crisp classifiers.
  4. Models are *adapted* to contexts by changing the threshold.
  5. ROC curves and other plots and metrics *evaluate* model behaviour for a range of contexts, assuming a given threshold choice method will be used.

Contexts: types and representation

- Data shift (covariate, prior probability, concept drift, …).
  - Changes in p(X), p(Y), p(X|Y), p(Y|X), p(X,Y)
- Costs and utility functions.
  - Cost matrices, loss functions, reject costs, attribute costs, error tolerance…
- Uncertain, missing or noisy information
  - Noise or uncertainty degree, %missing values, missing attribute set, ...
- Representation change, constraints, background knowledge.
  - Granularity level, complex aggregates, attribute set, etc.
- Task change
  - Regression cut-offs, bins, number of classes or clusters, quantification, …

Contexts: types and representation

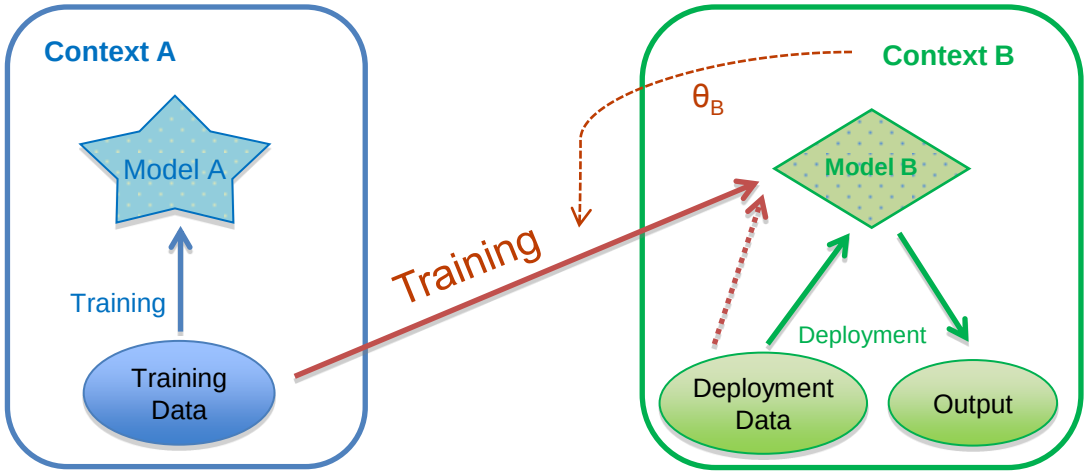
- Is the context absolute or relative to the original context?
  - Absolute:
    - E.g. in context B positive class is three times more likely than negative class.
  - Relative:
    - E.g. positive class in context B is three times more likely than in the original context A.
- Is the context given or inferred?
  - Given:
    - E.g.: cost information, cut-off, attribute set, …
  - Inferred (from the deployment data or a small labelled dataset):
    - E.g.: p(X), % of missing data, class proportion, …
- Is the context changing once for each dataset or for each example?
  - If the context changes for each example,
    - a non-systematic approach becomes very problematic.
    - context inference is more difficult.

Contexts: types and representation

- A context θ is a tuple of one or more values, discrete or numerical, that represent or summarise contextual information.
  - Examples:
    - Contexts are cities and temperatures:
      - θ_A= ⟨Nancy, 20⟩ is a context, while θ_B = ⟨Valencia, 30⟩ is another context.
    - Contexts are cost proportions.
      - θ = ⟨c⟩ where c is a cost proportion or a skew or a class prior.
    - Contexts are attribute granularity.
      - θ = ⟨week, city, women, category⟩ to specify granularities for dimensions time, store, customer and product, respectively.
    - Contexts are error tolerance.
      - θ = ⟨20%⟩ to specify that up to 20% of regression error is acceptable.

Adaptation procedures

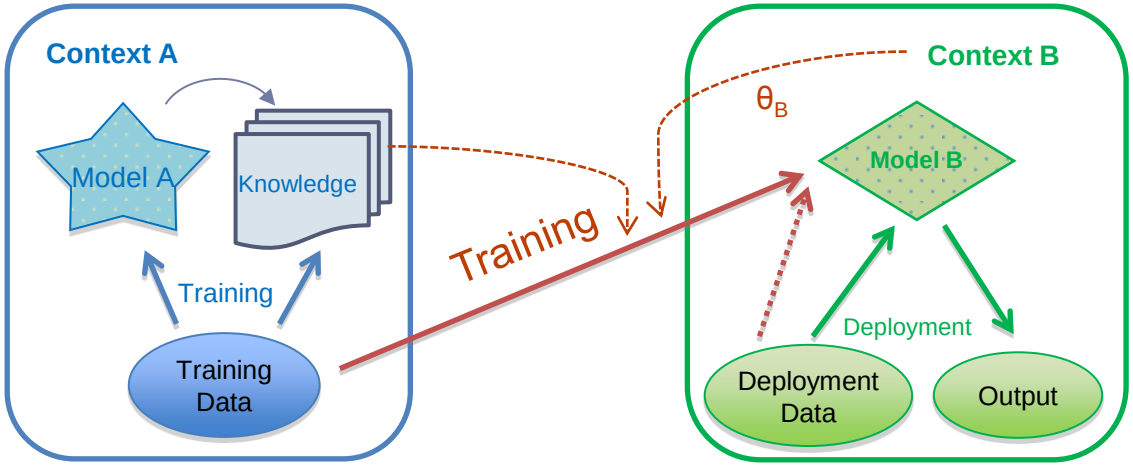
- **Retraining**: Train another model using the available (old and possibly new) data and the new context into account.



  - The original model is discarded (no knowledge reuse).
  - If there is plenty of new data, this is a reasonable approach.
  - Not very efficient if the context changes again and again (e.g., for each example).
  - The training data may have been lost or may not exist (the models may have been created or integrated by human experts).
  - May lead to context overfitting.

Adaptation procedures

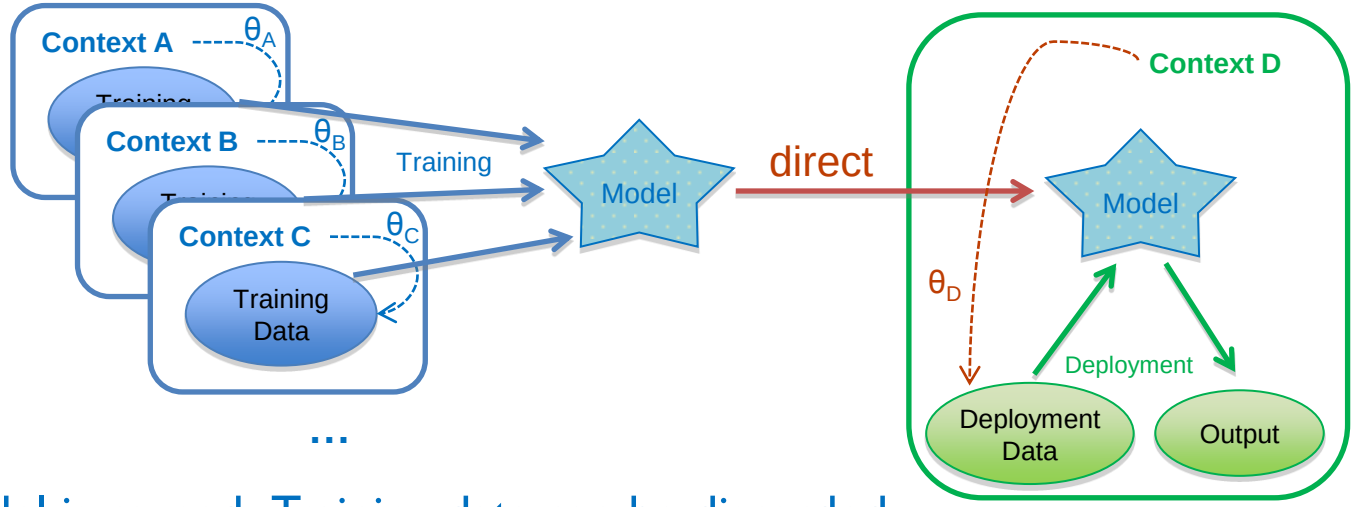
- **Retraining with knowledge transfer**: Train another model using (or tranferring) part of the knowledge from the original context.



  - Parts of the original model or other kinds of knowledge is still reused.
    - Instance-transfer (Pan & Yang 2010).
    - Feature-representation-transfer (Pan & Yang 2010).
    - Parameter-transfer (Pan & Yang 2010).
    - Relational-knowlege-transfer (Pan & Yang 2010).
    - Prediction-transfer: the original model is used to label examples (mimetism).

Adaptation procedures

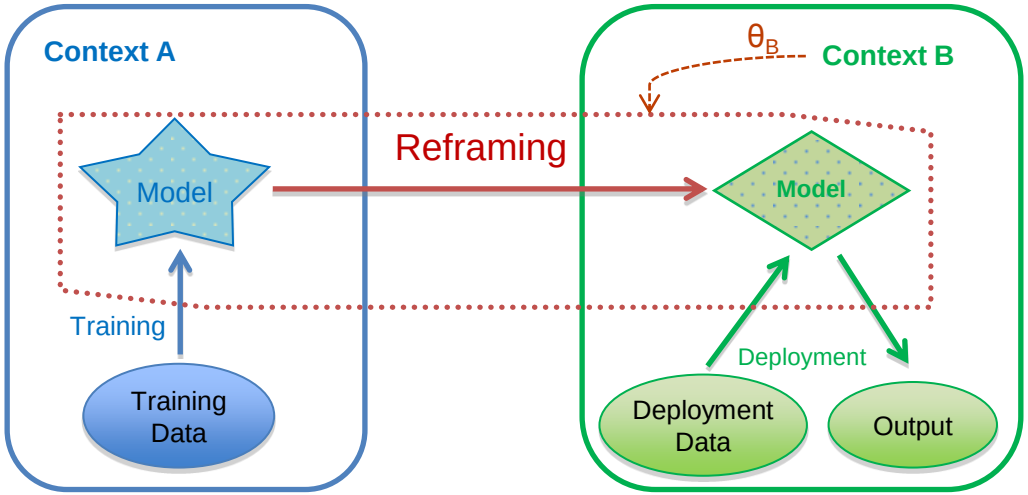
- **Context-as-feature:** the parameters of the context are added as features to the training data.



  - Model is reused. Training data can be discarded.
  - Requires several contexts during training in order to generalise the feature.
  - Makes more sense when there is a different context per example.
  - The context works as a "second-order" feature, regulating how the other features should be used. Not many machine learning techniques are able to deal with this kind of pattern.

Adaptation procedures

- **Reframing:** process of applying an existing model to the new operating context by the proper transformation of inputs, outputs and/or patterns.



  - Model is reused. Training data can be discarded.
  - The reframing process is designed to be systematic (and automated), using θ.
  - Only one original context is needed.

Versatile model

- A versatile model is a model that captures **more information than needed and/or generalises further than strictly necessary for the original context** in order to be prepared to be reframed for a new context.

- Examples:
  - Generative models over discriminative models.
  - Scoring classifiers over crisp classifiers.
  - Models gathering statistics (means, co-variances, etc.) about the inputs/output.
  - Unpruned trees over pruned trees.
  - Models that take different kinds of features.
  - Hierarchical clustering over clustering methods with a fixed no. of clusters.

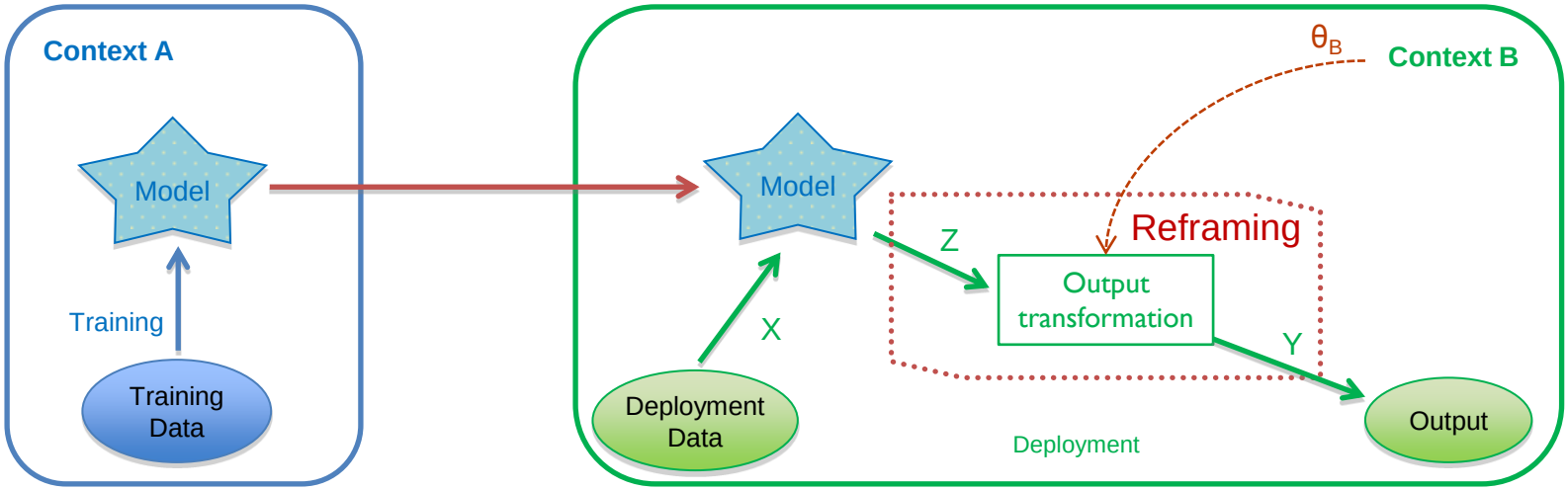
Versatile model

- How can we generate more versatile models?
  - Redefine learning algorithms and models, so that they include more information.
    - E.g., keep some of the information used during learning (densities, clusters, alternative rules, etc.).
  - Annotate models as a postprocess.
    - E.g., include statistics at each split of a decision tree.
  - Enrich them using the training or a validation dataset.
    - E.g., calibration.

- The knowledge is not gathered in a separate way from the model (as in knowledge transfer)
- This knowledge is embedded in the model so that its adaptation can be automated.

Kinds of reframing

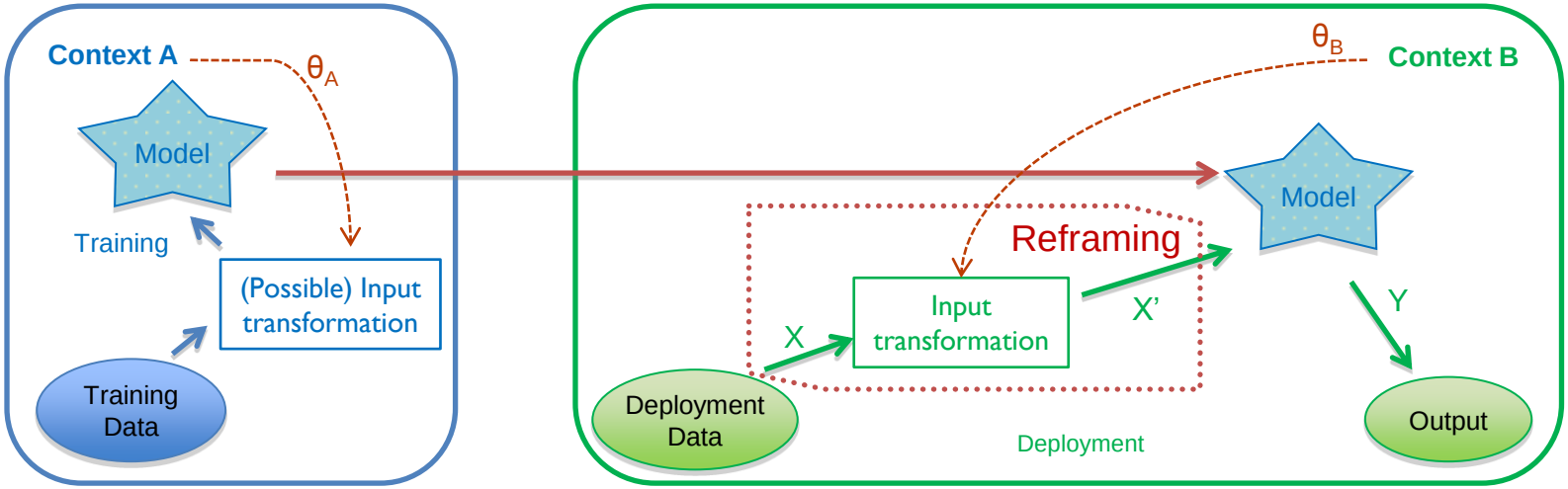
- Output reframing.
  - Outputs are reframed.



  - Examples and other names:
    - Use of ***threshold choice methods*** with scoring classifiers (as in ROC analysis).
    - Binarised regression problem (***cutoff*** from regression to classification).
    - ***Shifting*** the output to minimise expected cost in regression. By ***tuning*** (Bansal et al. 2008) or reframing (Hernandez-Orallo 2014).

Kinds of reframing

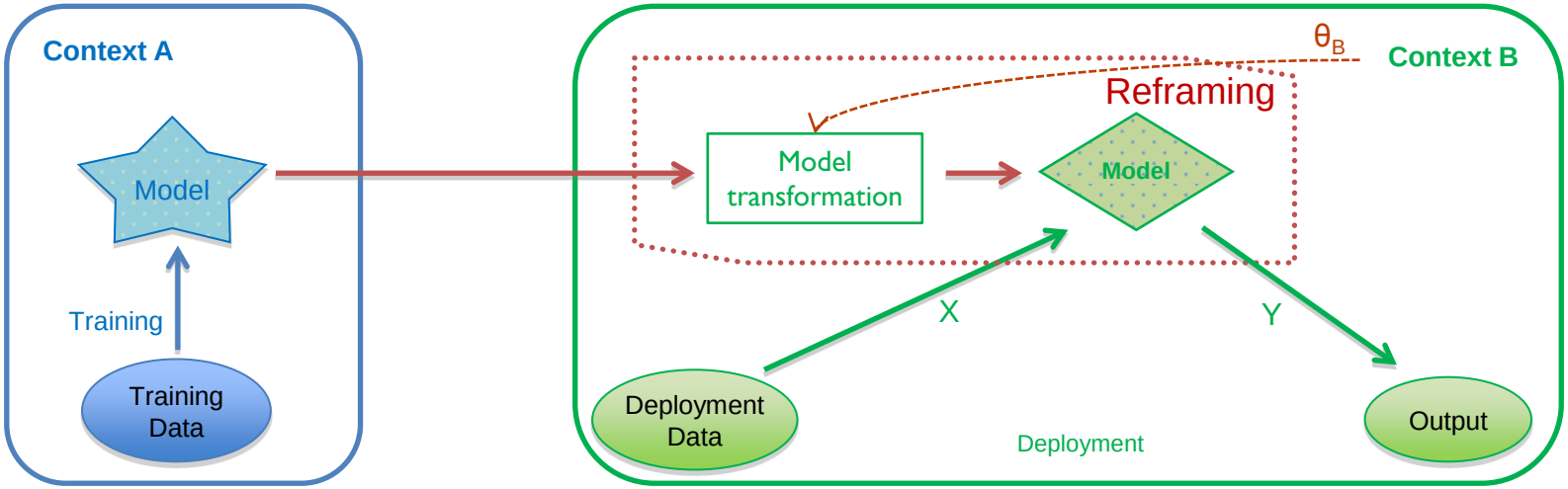
- Input reframing.
  - Inputs are reframed.



  - Examples and other names:
    - Use of quantiles (El Jelali et al. 2013).
    - Feature shift (Ahmed et al 2014)

Kinds of reframing

- Structural reframing.
  - The model is reframed.



  - Examples and other names:
    - Relabelling (e.g., using a small labelled dataset)
    - Postpruning (during deployment).

Evaluation with context changes

- The performance of a model *m* on a data *D* can be evaluated for a single context θ using a reframing procedure *R*.

$$Q(R, m, D, \theta)$$

- If contexts change systematically, we want to see model performance *using* a reframing procedure for a *range of operating contexts*:
  - With a context plot: context on one or more axes and Q on another axis.
    - Dominance regions can be visualised.
  - How can we summarise a curve?

$$L(R, m, D, \mathbb{C}, w) \triangleq \int_{\theta \in \mathbb{C}} Q(R, m, D, \theta) w(\theta) d\theta$$

    - A range of contexts is given by a set of contexts $\mathbb{C}$ and a distribution *w* over them.

Evaluation with context changes

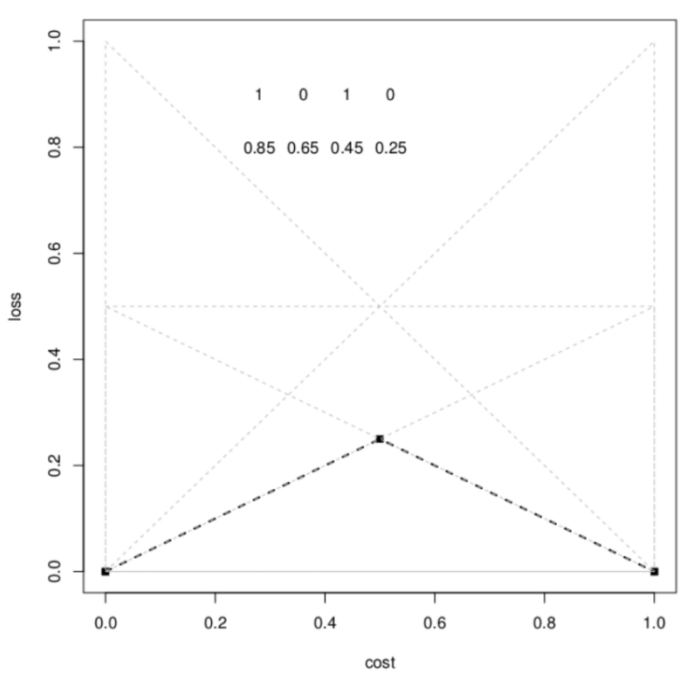
- Example: classical cost curves are context plots.

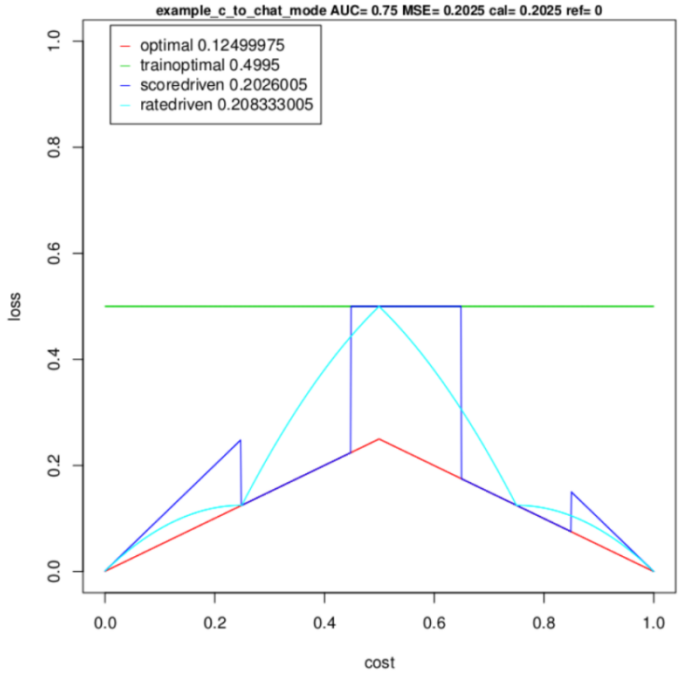
F_0:TPR or sensitivity if threshold is set on t
$1-F_1$:TNR or specificity if threshold is set on t

$$Q(t;c) = 2\{c\pi_0(1 - F_0(t)) + (1 - c)\pi_1 F_1(t)\}$$

c is the context

  - Many other curves are possible if the reframing procedure is different.
    - In this case, several threshold choice methods on the right.





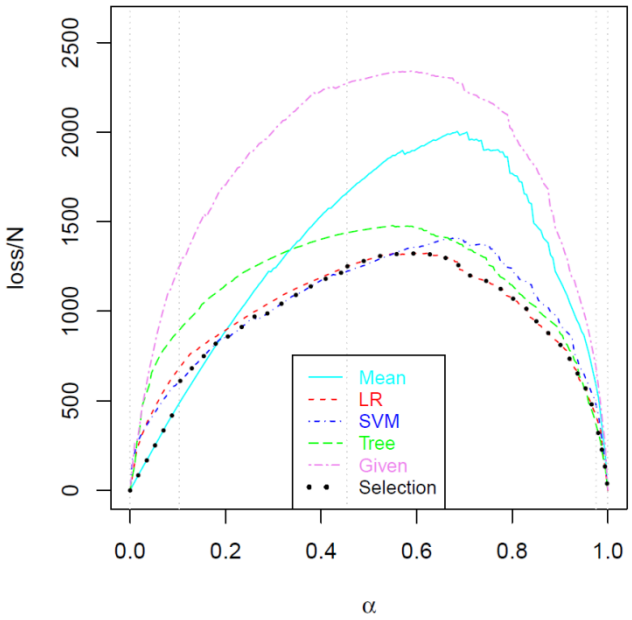
Evaluation with context changes

- Example: regression asymmetric costs
  - For instance, using asymmetric absolute cost (Lin-Lin) for regression:

$$\ell_\alpha^A(\hat{y}, y) \triangleq \begin{cases} 2\alpha(y - \hat{y}) \\ 2(1-\alpha)(\hat{y} - y) \end{cases}$$

α is the context

  - Regression cost curves:

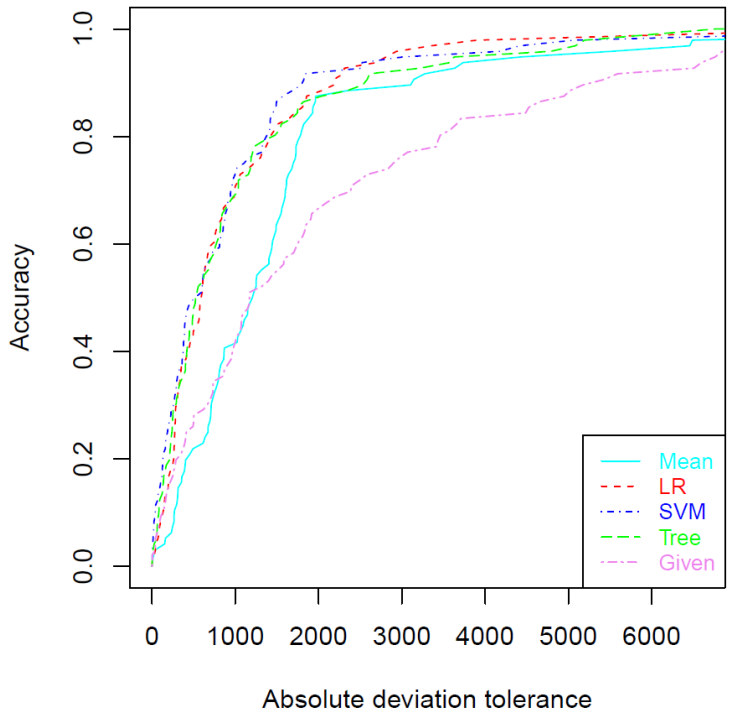


Evaluation with context changes

- Example: REC curves (tolerance level)

$$Acc = \mathbf{1}[\,|y - \hat{y}| \leq tolerance\,]$$

tolerance is the context



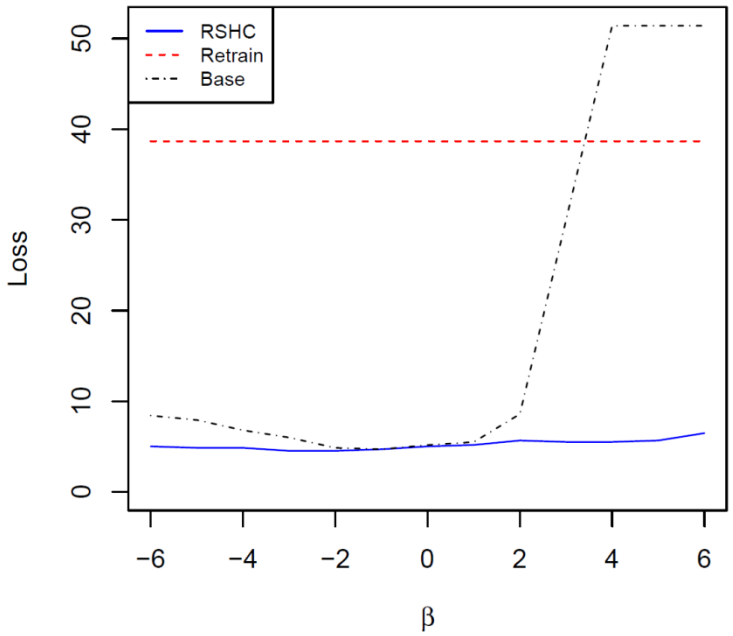
Evaluation with context changes

- Example: attribute shift
  - One or more attributes have a constant shift (Ahmed et al. 2014):

$$x' \leftarrow x + \beta$$

β is the context

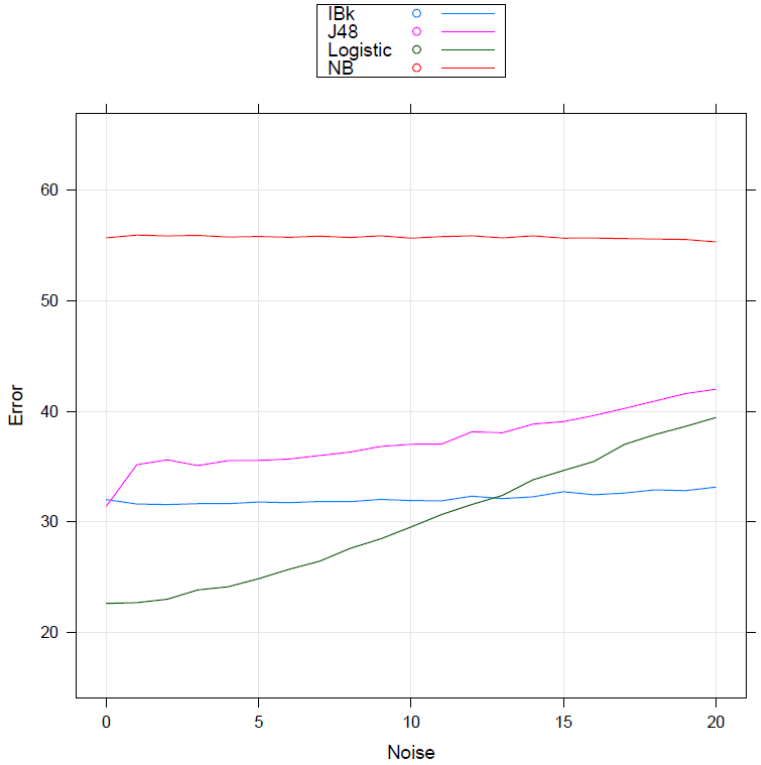
  - In this context plot, we compare retraining with a reframing approach.



Evaluation with context changes

- Example: noise levels (Ferri et al. 2014)
  - Data may have different levels of noise.

level of noise is the context



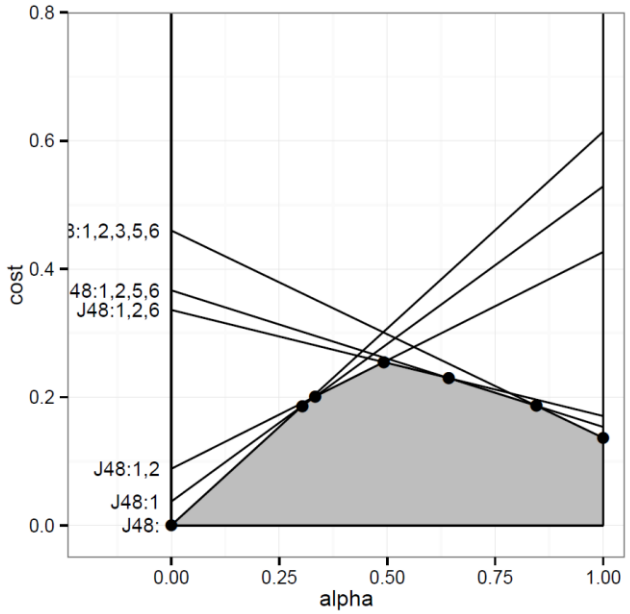
Evaluation with context changes

- Example: misclassification cost (MC) vs attribute test cost (TC):

$$JC_i \triangleq \alpha_i \cdot MC_i + (1 - \alpha_i) \cdot TC_i$$

α is the context

  - Different attribute subsets lead to different cost lines:



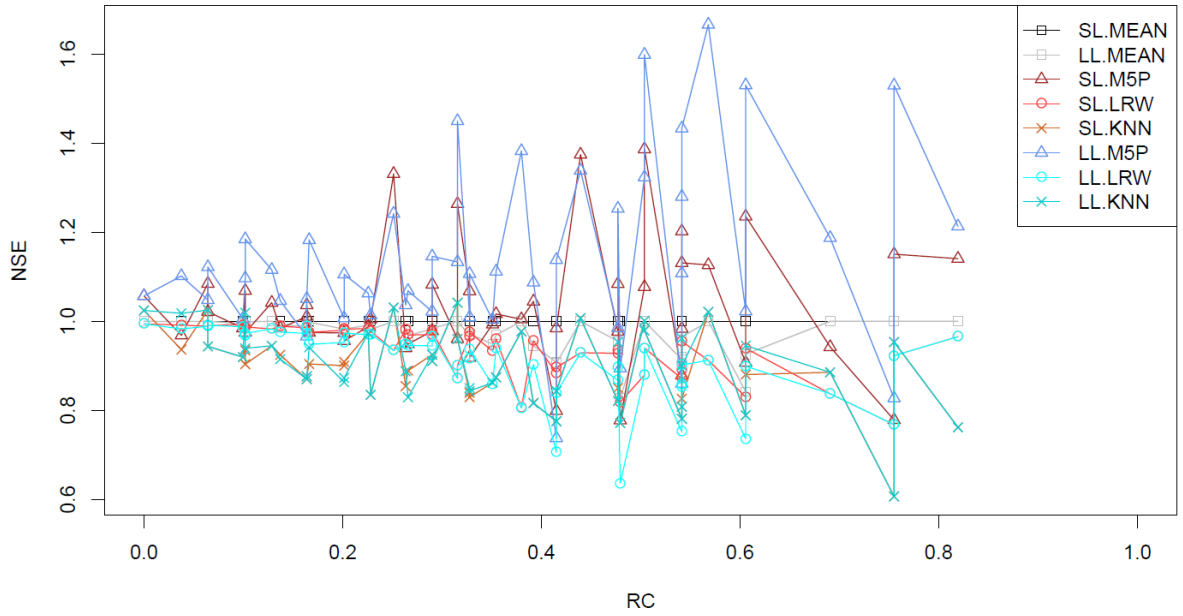
Evaluation with context changes

- Example: multidimensional (attributes are hierarchical dimensions)

$$\langle l_1, \ldots, l_d \rangle, \ with \ each \ l_i \in h(X_i)$$

This tuple of levels is the context

  - To make the plot simpler, we use a Reduction Coefficient (RC), which expresses the level of aggregation of the data (from 0 to 1).

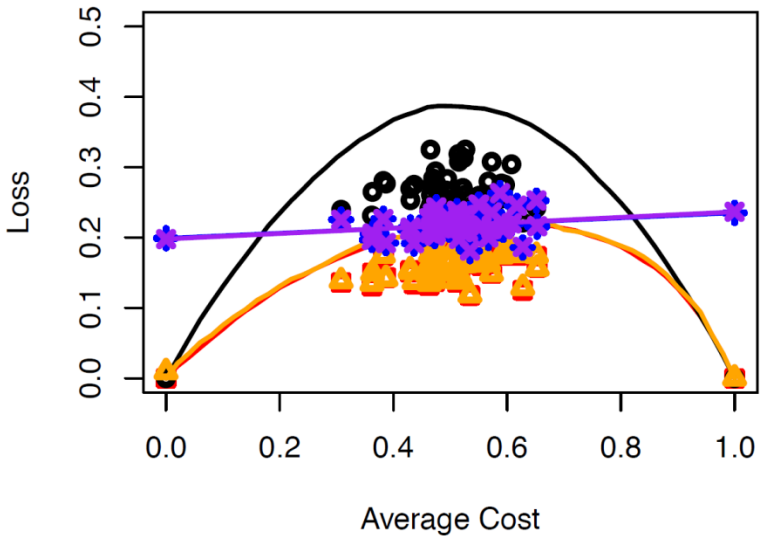


RC is a simplification of the context

Evaluation with context changes

- Example: multilabel (Al-Otaibi 2014)
  - Costs per each label are introduced
  - Different colours represent different threshold choice methods.

The tuple of costs for all labels is the context



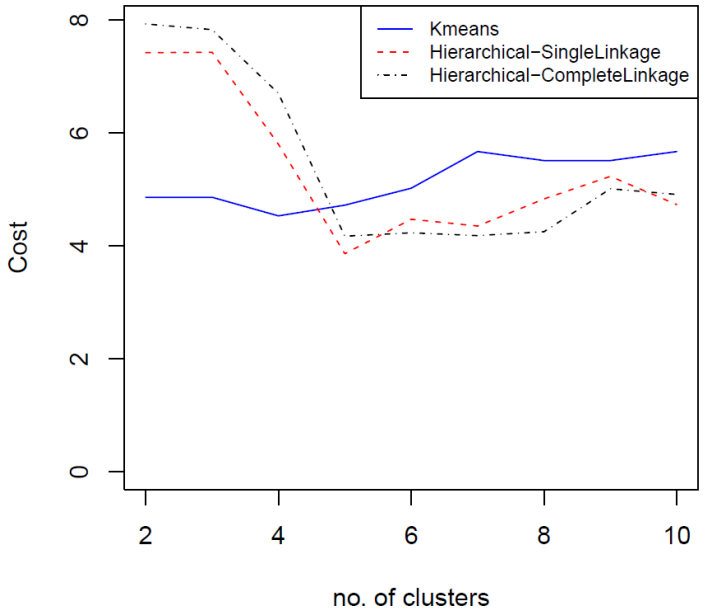
The "average cost" is a simplification for the context

- Curves are for cases where the costs are equal for all labels. Clouds are for cases where cost are different for each label (but the average is on the *x*-axis).

Evaluation with context changes

- Example: clustering algorithms depending on number of clusters
  - Different clustering algorithms:

The no. of clusters is the context



The "cost" can be any clustering performance metric, such as Davies-Bouldin index, the Dunn index or the Silhouette coefficient.

  - Kmeans is rerun (retrained) with different values for K.
  - Hierarchical methods are versatile models working for several contexts.

Related areas

- Data shift.
- Domain adaptation.
- Cost-sensitive learning.
- Learning with noisy data.
- Transfer learning.
- Multi-task learning.
- Transportability.
- Context-aware computing.
- Mimetic models.
- Theory revision.
- ROC analysis and cost plots.

Related areas

- A reframing perspective is distinctive:
  - Contexts are clearly identified and parameterised.
  - It's not a one-to-one occasional transfer but a systematic application.
  - There can be several reframing methods for the same model and data, leading to different results.
  - Models are learnt in one context and task but kept for many contexts.
  - Performance is analysed in a range of contexts.
  - Models are reused.

Conclusions

- Disposing validated models again and again is not cost-efficient.
  - Reusing models seems more appealing.
- Versatile models should be as general as possible to cope with a range of contexts.
  - Validation has to take this range of contexts into account.
- Model deployment is crucial.
  - Models become good or bad for a context depending on the deployment procedure we are using.
- But don't be blinded by reframing.
  - We should always consider the trade-off between retraining and reframing (and other possible options).