Learning Stochastic Edit Distance from Structured Data: Application in Music Retrieval

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Outline

1. Tree Edit Distance
2. Stochastic Extension
3. Music Database
4. Experiments
5. Future work

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Tree Edit Distance

- The Tree Edit Distance is a generalization of the (String) Edit distance where the edit operations take place over trees.
- The tree edit operations are:
  - Substitution: Change the label of a tree node ($a \rightarrow b$)
  - Deletion: The children will become children of their father ($b \rightarrow \epsilon$)
  - Insertion: Some of the sibling will become children of the inserted node ($\epsilon \rightarrow b$)

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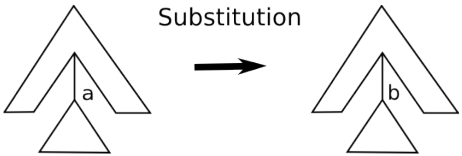

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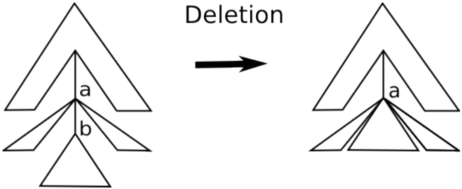

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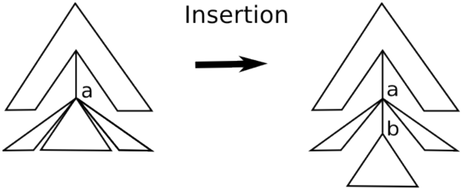

- Let S (script) be a sequence $s_1, \ldots, s_n$ of edit operations that transforms a tree into another
- Let γ be a weight function that assigns to each edit operation $(a \rightarrow b)$ a nonnegative real number $\gamma(a \rightarrow b)$.
- Let $\gamma(S) = \sum_{s_i \in S} \gamma(s_i)$

Definition:

The tree edit distance is a function such that:

$$\delta(t_1, t_2) = \min\{\gamma(S) | S \text{ is a script that transforms } t_1 \text{ into } t_2\}$$

- This can be computed [Zhang and Shasha, 89] in: $O(|t_1||t_2| \min(depth(t_1), leaves(t_1)) \min(depth(t_2), leaves(t_2)))$

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The Stochastic Edit Distance

- The weights are probabilities
  - $\gamma(a \rightarrow b)$: substitution probability
  - $\gamma(\epsilon \rightarrow b)$: insertion probability
  - $\gamma(a \rightarrow \epsilon)$: deletion probability
  - γ: ending probability
- Now $\gamma(S) = \prod_{s_i \in S} \gamma(s_i) \cdot \gamma$

Definition:

The stochastic tree edit distance (δ) is a function such that:

$$p(t_1, t_2) = \sum_{S \in S(t_1 \rightarrow t_2)} \gamma(S) \qquad \delta(t_1, t_2) = -\log p(t_1, t_2)$$

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Normalization

Depending on the framework we have to ensure:

- In the generative model:

$$\sum_{t_1,t_2} p(t_1, t_2) = 1$$

$$\sum_{a,b} \gamma(a \to b) + \sum_{a} \gamma(a \to \epsilon) + \sum_{b} \gamma(\epsilon \to b) + \gamma = 1$$

- In the discriminative model:

$$\sum_{t_2} p(t_1, t_2) = 1 \quad \forall t_1$$

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Which edition weights should we use?

- Usually an expert fixes them
- Why not learn them?
- In a probabilistic framework the immediate criterium is to search for the weights that maximize the expectation of a training set
- This was done for strings by:
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EM Algorithm-based Approach

We adapt EM algorithm to the learning of $\delta(\cdot, \cdot)$ from (input,output) tree pairs.

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- Function expectation counts the number of times each operation is used for changing an input tree into an output one
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Application: Music Recognition

- The corpus consists of a set of monophonic 8-12 bar incipits of 20 worldwide well known tunes of different musical genres: (Bolero, Cucaracha, Jinglebells, Guantanamera, Happy Birthday, Yesterday, ...)
- For each song a canonic tune was created by writing the score in a musical notation application and exported to MIDI and MP3 format
- The MP3 files were given to some amateur and professional musicians who listened to each song (mainly to identify the requested range of the tune to be played) and played in MIDI keyboard and guitars several times the same tune with different embellishments. We colected 20 interpretations of each tune.
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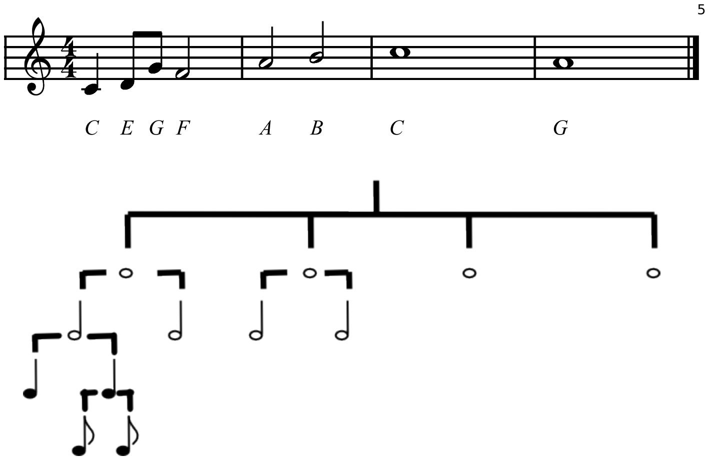
Objective:

- to learn a stochastic tree edit distance in order to recognize the song played by musicians
- Use of a tree-structured representation

Music Representation



- Logarithmic scale of musical notes is represented by the depth in the tree

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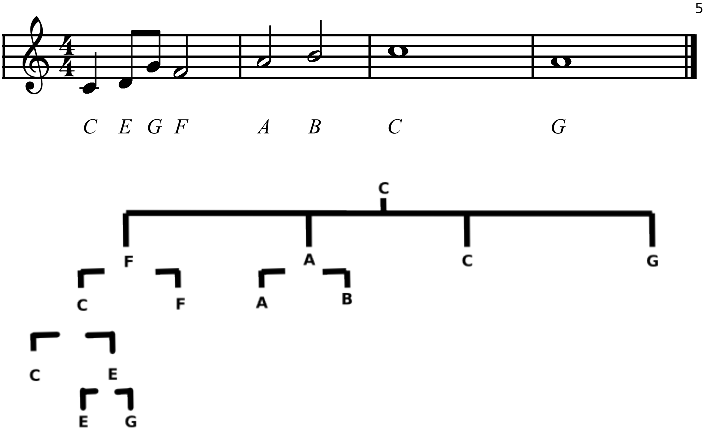

- Leaves are labeled by the pitch of the notes
- Internal nodes are labeled according to musical rules

Outline

Experimental Setup

- We exclude the canonic tunes and we use a 5-fold cross validation on the remaining set of tunes
- Learning
  - For each tune in the training set we create a pair `(canonic-tune, tune)`.
  - We learn the edit weight from these learning tree pairs.
- Testing
  - We use a 1-NN with the canonic tunes as a set of prototypes
  - We classify each tune of the test set in the class of the canonic tune which is at the minimal stochastic edit distance
- We compare the results obtained with the same testing procedure using non learned diagonal weight matrix.

Results

- 80% of correct classification learning the edit weight
- 51% with a non learned diagonal weight matrix

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  - Apply the learning method to other problems
    - already done in image recognition
  - Taking into account the context of the operations
  - Learning stochastic tree transducers
  - Apply the ideas to other structures
    - subclases of graphs
    - multistrings (some work in progress)
- Related with Music
  - Larger datasets
  - from sound instead of MIDI files
    - it is a task in a large spanish project: transcription, interactivity

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