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# In support of self-assessment – exploiting available information from tools

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## Tool Performance

The quality of output from tools for automatic analysis/processing of natural language hardly ever reaches 100% and depends on several factors:

- The annotation task (e.g. part-of-speech tagging vs. parsing)
- The input data: For in-domain input performance is reasonably well (comparable to results from literature). Out-of-domain input likely results in a drop of performance.

This might result in trust issues for potential users, especially when the tool is applied as an intermediate step in a processing chain or in a new out-of-domain setting. Furthermore, workload for the user might increase by a need for additional evaluation to find the best tool for the task or extensive correction steps after processing to find and correct errors.

**Transparency** (and usability) for the user can be increased by:

- A thorough tool documentation, specifying the standard domain of input data and the functional range: "What this tool will not be able to do…"
- Propagating available confidence information from the tool to the user

## Preserving Tool Confidence

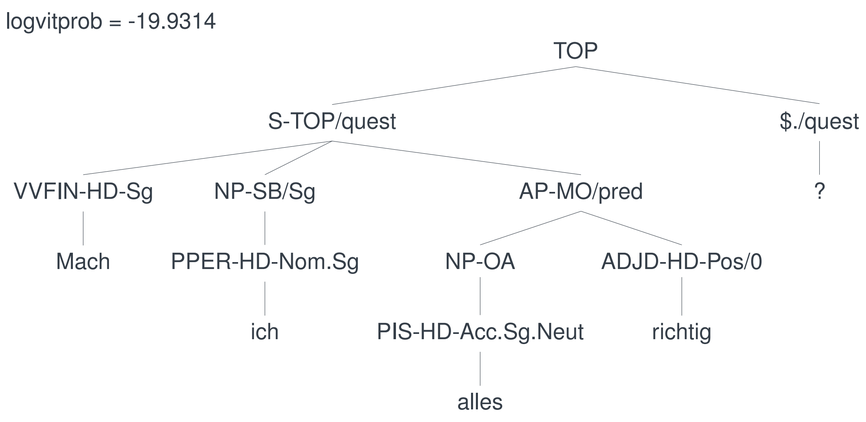
Many automatic tools are internally aware of a relative reliability of their output since they make use of probabilities and forced guessing to decide on a single analysis or create n-best-lists. Others introduce a default handling of unexpected input, from which a reliability estimation can be derived. In most cases this information is discarded after deciding on a single prediction and never included in a tool's output. In our opinion this represents a serious loss of valuable meta-information.

## Confidence as Annotation Layer

We suggest to include a tool's confidence estimations directly in its output as additional (meta-)annotation layers. This allows for a series of straightforward applications:

- Visualizations can easily use this information to present visual distinctions or filters based on different levels of confidence.
- When using sophisticated corpus-query tools the user is able to restrict queries to annotations with desired reliability via search constraints.

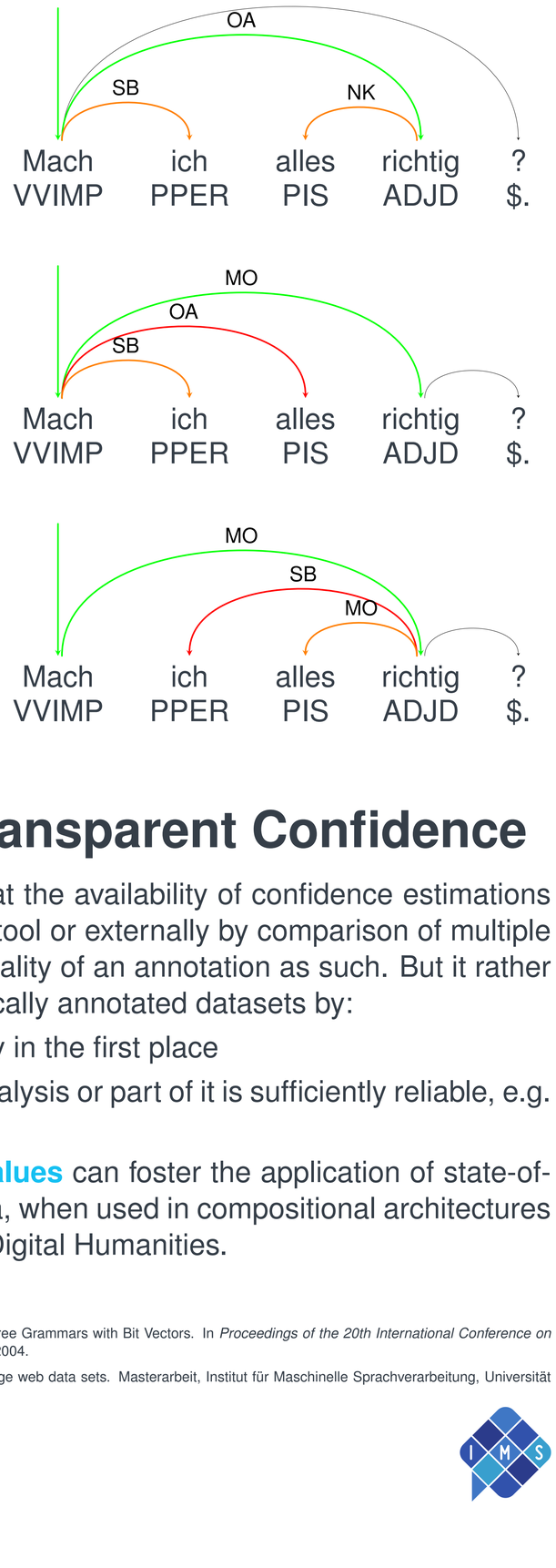
⇒ Ultimately the availability of those values as annotations should aid users in finding interesting data wrt to a certain range or level of confidence.




| Sentence | IMSTrans | Mate | Turbo |
|---|---|---|---|
| Mach | root | root | root |
| ich | 1 | 1 | 4 |
| alles | 4 | 1 | 4 |
| richtig | 1 | 1 | 1 |
| ? | 1 | 4 | 4 |

Examples of a sentence parsed by constituency and dependency grammar with several automatic tools and different confidence estimations:

- On the left entries of BitPar's [1] n-best list and the respective raw probabilities for each tree as examples for **internal** confidence.
- Above and to the right different parses from `IMSTrans`, `Mate Tools` and `TurboParser` with **external** confidence estimations for attachment created by comparing the individual outputs [2].




## Interpretation of Confidence Values

Unprocessed usage of raw confidence values in cases where they are already available (e.g. probabilities produced by BitPar [1] for the left trees in above figure) faces certain limitations in terms of usability:

- Range of possible values can be vastly different across and within tools
- Granularity of analysis can differ between tools (e.g. confidence for individual arcs in a dependency parse versus the entire tree)

⇒ Currently real comparability is only possible for confidence values produced by a single tool for the same kind of decisions, such as n-best lists.

We therefore propose to normalize to a simple scale to allow for an easier general interpretability of individual confidence estimations as well as a basic comparability between different tools. As such a tool should project its confidence estimation into classic probability values in the closed interval `[0,1]` (as a confidence scale from "pure guesswork" to "being sure").

## Advantages of Transparent Confidence

It is important to keep in mind that the availability of confidence estimations (obtained either internally from a tool or externally by comparison of multiple outputs) does not increase the quality of an annotation as such. But it rather boosts usability of large automatically annotated datasets by:

- Raising awareness wrt reliability in the first place
- Helping users to assess if an analysis or part of it is sufficiently reliable, e.g. for a specific downstream task

Thus **transparent confidence values** can foster the application of state-of-the art tools on out of domain data, when used in compositional architectures and in related fields such as the Digital Humanities.

[1] Helmut Schmid. Efficient Parsing of Highly Ambiguous Context-Free Grammars with Bit Vectors. In *Proceedings of the 20th International Conference on Computational Linguistics (COLING 2004)*, Geneva, Switzerland, 2004.

[2] Tanja George. Confidence estimation for automatic parsing of large web data sets. Masterarbeit, Institut für Maschinelle Sprachverarbeitung, Universität Stuttgart, 2016.

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