TUTA1 at the NTCIR-11 Temporal Task
Exploring Temporal Information for TQIC

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Abstract
For NTCIR-11 Temporal subtask Temporal Query Intent Classification (TQIC), we carefully study tempo-
ral attributes in the dry-run features, explore time gap, verb tense, lemma and named entity as temporal
features, and build supervised and semi-supervised linear classifiers. We report the Precision and Over Precision
scores through RUN-1 to RUN-6 as well as a baseline RUN-4. We compare the performance with respect to different
parameter and learning algorithm configurations, and analyze the TQIC errors. We find the time gap and verb tense
features with a supervised classifier are effective in separating the Past and Future queries, while the lemma and
named entity feature could help predicting the Recent and Atemporal queries with a semi-supervised classifier.

Introduction
The TUTA1 group at The University of Tokushima participated in two subtasks, Temporal Query In-
tent Classification (TQIC) and Temporal Information Retrieval (TIR), of the new pilot task Temporal Information
Access[1] (Temporal) at NTCIR-11. The TQIC subtask focuses on the identification of user’s temporal intent given
the query string and submission date, across four temporal categories Past, Recent, Future, and Atemporal.

Challenges
1. What are effective temporal features in search queries?
2. How to model temporal information in the background?

Temporal Feature Extraction
Because query strings are usually very short (4.2 words in dry-run on average), to find useful temporal
features in queries and to explore the background information seem to be prominent in this subtask.

AOL 500K User Session Collection
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Temporal Intent Classifiers

• Supervised classifier: Logistic Regression Classifier in scikit-learn 0.13.0
• Semi-supervised classifier: Linear SVM Classifier in SVMlight[3].

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Table 2: TQIC runs.

<table>
<thead>
<tr>
<th>Run Feature</th>
<th>Dataset</th>
<th>Classifier</th>
<th>Hyper Parameter</th>
</tr>
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<tbody>
<tr>
<td>All temporal features</td>
<td>Dry-run</td>
<td>LGR</td>
<td>C = 30, penalty = λ</td>
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<tr>
<td>All temporal features</td>
<td>Dry-run, AOL SVMlin</td>
<td>A = 2, W = 0.1, U = 3, R = 0.01</td>
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<td>Lemma &amp; named entity</td>
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Error Analysis
Recent and Atemporal seem more difficult to predict than Past and Future. In each sub-
plot, the cell located at row i and column j corre-

Table 3: Precision scores. Wilcoxon signed-rank test with p < 0.05 is em-
ployed for statistical significance test: superscripts 1, 2, 3 indicate statistically
significant differences to RUN-1, RUN-2, and RUN-3 respectively.

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Figure 2: Confusion matrices for 4 Runs.

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Conclusions

• Three temporal features were extracted for temporal information representation in search queries.
• A semi-supervised classifier was developed to expand the temporal feature on an unlabeled dataset.
• Recent-Future, Attemporal-Recent, and Future-Recent counted a big part of the mis-classification.

Forthcoming Research
Our future work will focus on investigating temporal information in lemmas and named entities.
Meanwhile, methods for preventing the learning algorithms from over-fitting will also be employed.

References