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CoT or ReAct: Evaluating ReAct-Based LLM Reasoning for Korean Date and Schedule Processing

Yein Oh, Jisu Kim, Jihyun Jung, Sooyeon Park

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I. Introduction

Research Background – Korean Date and Schedule Processing

- NLP-based **schedule calculation** and **time normalization** are core functions in various AI services.
- Korean presents a high degree of difficulty due to complex constraints, including
  - **relative tense**
  - **complex combination of public holidays, weekdays, and intervals**
- Existing LLM-based approaches using **few-shot learning**, **Chain-of-Thought (CoT)** reasoning, and **fixed JSON output schemas** have achieved a moderate level of performance.
- However, they have shown **limitations** in consistently and accurately satisfying these constraints.

Research Background – Korean Date and Schedule Processing

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※ [1] Source: Jeong, Y. S. et al. (2022). Rule-based Normalization of Relative Temporal Information.

Research Background – Korean Date and Schedule Processing

- However, they have shown **limitations** in consistently and accurately satisfying these constraints.

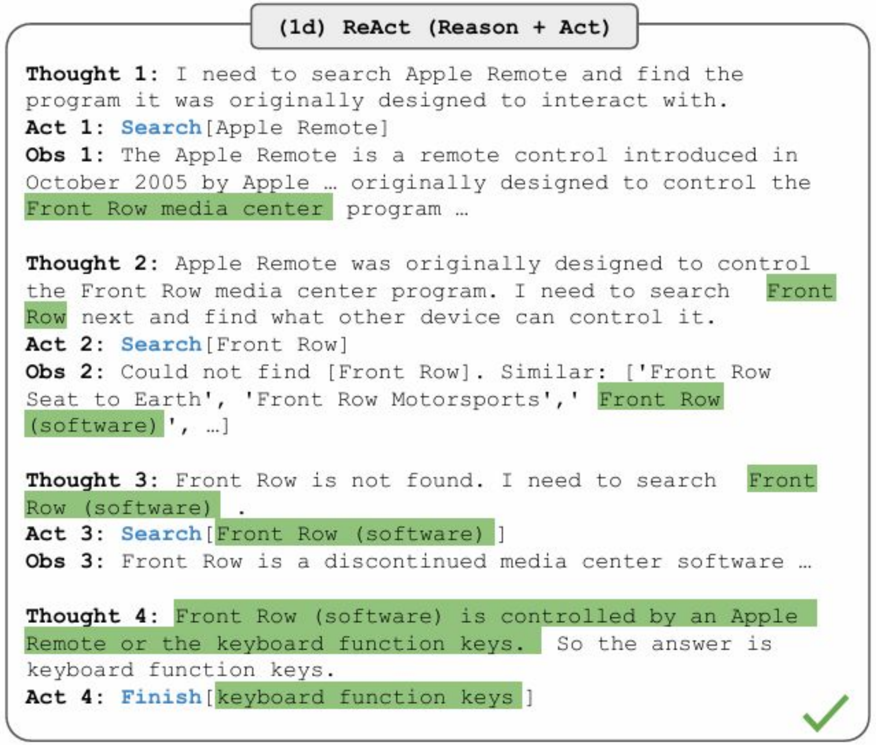
Attribute	Accuracy(%)
year	73.14%
month	61.21%
day	74.57%
week	91.39%
hour	75.00%
minute	50.00%
second	100.00%

※ [1] Source: Jeong, Y. S. et al. (2022). Rule-based Normalization of Relative Temporal Information.

Proposal – ReAct

- ReAct = **Reason** + **Act**
  - Loop structure of “**Reasoning**” ↔ “**Action**” ↔ “**Observation**”
  - Incorporates external information through tool calls

    → Enables more structured and logical reasoning compared to simple CoT prompting



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※ [2] Source: Yao et al. (2023). *ReAct: Synergizing Reasoning and Acting in Language Models*.

II. Tasks

Three Tasks for Evaluating Korean Temporal Reasoning

- **Constraint-based Korean Schedule Generation**
  : to accurately **interpret complex temporal and scheduling constraints** within a **Korean** natural language query, in order to generate a list of dates that satisfies all specified conditions
  - Input: "수능 다음날부터 공휴일 제외하고 3일 간격으로 2개 날짜 제안해줘"
  - Output: a **list of dates** that **satisfy the given constraints**

- **Three Tasks (Increasing in Complexity)**
  - **T1**: Convert relative time expressions, **phrases** → absolute dates
  - **T2**: Convert relative time expressions, grounded in context, using complete **sentences** → absolute dates
  - **T3**: Generate **schedules** satisfying **multiple interacting constraints**

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Task Details

To compare CoT vs. ReAct robustness, we design **three tasks**, each isolating a different reasoning challenge:

- **T1 — Date Normalization (Phrases)**
  - Input: **standalone relative expression**
    - e.g., “이번 달 마지막 수요일”
  - Requires sequential temporal arithmetic (month-end → next weekday).
  - Output: **one absolute date** (YYYY-MM-DD).
  - Tests **core temporal arithmetic** without linguistic ambiguity.
- **T2 — Date Normalization Using Sentences**
  - Input: **full natural-language sentences** containing temporal phrases.
    - e.g., “2주 뒤인데, 만약 그날이 공휴일이면 다음 평일로 해줘.”
  - Requires finding the relevant span **before** calculating the date.
  - Same output format as T1.
  - Tests **linguistic grounding + disambiguation**.
- **T3 — Constraint-based Schedule Generation**
  - Input: **multiple explicit constraints** (intervals, weekdays, exclusions).
    - e.g. “내년 1월 첫 번째 금요일부터 시작해서 5일 간격으로 4회 일정 잡아주세요”
  - Must iteratively generate dates and filter invalid ones.
  - Output: **list of dates**.
  - Tests **long-horizon reasoning, constraint satisfaction, rule integration**.

Hypotheses

- **H1**: The more **complex** the constraints, the **higher** the **accuracy** and constraints satisfaction in **ReAct** Agent.
- **H2**: **ReAct** may **increase response time** and **token usage**, but shows **Pareto-efficient** accuracy-to-cost performance.

III. Methodology

CoT: Chain-of-Thought Reasoning

Few-shot Chain-of-Thought (CoT) Prompting	**Purely Internal Reasoning**	**Task-specific Formatting**	**Purpose as a Baseline**
• Each task uses a small set of demonstrations showing the desired reasoning format. • Model is instructed to produce step-by-step reasoning followed by a final answer.	• All computations occur inside the LLM. • No external tools, symbolic modules, calculators, or validation steps. • Represents the natural behavior of text-only reasoning.	• T1 & T2: Output is a **single normalized date** (YYYY-MM-DD). • T3: Output is a **sequence of dates** satisfying constraints. • Prompts differ only in the input/output description; core CoT style is consistent.	• Provides a clean comparison against ReAct. • Highlights how agentic stepwise execution can improve temporal reasoning beyond static CoT.

ReAct Model: Thought → Action → Observation Loop

Core Mechanism

- Alternates between:

  Thought (internal reasoning) → **Action** (tool call) → **Observation** (tool output).
- Modular design: planner (thought), tool executor (action), decision module (observation evaluation).
- Same loop for all tasks, but behavior differs by task complexity.

Tools Used Across Tasks

- **Calculator** — date arithmetic (offsets, intervals, weekday shifts).
- **Calendar_db** — holidays, lunar/solar terms, anniversaries.
- **Search** — event lookup when rules are non-deterministic.
- Modular separation supports multi-step reasoning in T3 while keeping T1/T2 lightweight.

T1: Phrase-Level Date Normalization	T2: Sentence-Level Date Normalization	T3: Constraint-Based Schedule Generation
• Input: isolated temporal phrase. • Single-step reasoning → one tool call (e.g., calculator, calendar_db). • No iteration needed; observation directly yields normalized date. • Focus: pure temporal arithmetic.	• Must first locate the temporal span inside a full sentence. • Thought module extracts the temporal phrase and reformulates it into canonical tool input. • One tool call → one observation → final normalized date. • Difference from T1: requires linguistic span identification before arithmetic.	• Fully iterative, multi-step reasoning loop. • Planner decides next action: ○ Find start date / Apply intervals / Check rule violations. • Observation is evaluated by decision module → returns structured state + continue/stop signal. • Loop continues until constraints are satisfied (or terminates if the 10-turn limit is exceeded).

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IV. Experiments

Experiment Design: Method Implementation

Comparison Setup

<table>
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<td>
Baseline (CoT)

Few-shot + Chain-of-Thought prompting
No tool use; all reasoning done internally
Fixed JSON output schema for all tasks
One-pass generation (no intermediate verification)

</td>
<td>
ReAct Agent (Method-Aligned)

Implements the Thought → Action → Observation loop
T1 / T2:

Single-step reasoning
Thought: interpret temporal phrase/sentence
Action: one call to calculator or calendar_db
Observation: tool returns the normalized date → final output

T3:

Fully iterative multi-step planning
Thought: decide next operation based on constraints & partial schedule
Action: tool calls for date arithmetic, holiday lookup, or external event search
Observation: decision module evaluates constraint satisfaction and updates state
Loop continues until a complete valid schedule is produced

Modular design separates planning, tool execution, and validation

</td>
</tr>
</table>

Experiment Design: Logistics

Datasets

- **T1:** 500 Korean relative-time *phrases* (single-date normalization)
- **T2:** 500 Korean relative-time *sentences* (embedded temporal span extraction)
- **T3:** 500 Korean multi-constraint scheduling queries (intervals, weekdays, holidays, counts)

Models Evaluated

- **GPT-4.1-mini** (via OpenAI API)
- **Solar Pro 2** (via Upstage API)

Experiment Design: Evaluation Metrics

Task Accuracy

- **T1 & T2 (Single-Date Tasks)**
  - Output: one ISO-8601 date
  - **Exact-match accuracy**: prediction must match gold date *exactly*
  - No credit for partial matches or ±1-day errors
- **T3 (Schedule Generation)**
  - Output: ordered list of dates
  - **Exact full-sequence match** required
  - Any mistake (wrong date, missing/extra dates, interval errors, constraint violation) → **failure**
  - ReAct exceeding **10-turn limit** also counted as failure

Efficiency Metrics

- **Latency**: wall-clock time from first prompt to final output
  - Captures extra overhead from multi-step reasoning in T3
- **Token Usage**: total prompt + completion tokens
  - Compares computational cost of CoT vs. ReAct reasoning loops

Overall Evaluation

- Accuracy = proportion of predictions passing the exact-match criteria
- Latency + token usage provide a measure of **efficiency vs. correctness trade-offs**

V. Results

T1 Performance

- **ReAct improves GPT's accuracy**:
  - GPT-ReAct outperformed GPT-CoT by **+4.0 points** (76.2% vs. 72.2%), a **statistically significant gain** ($p = .0018$)
  - Shows that ReAct meaningfully reduces single-event reasoning errors in GPT models
- **Solar models show a different trend**:
  - Solar-ReAct achieved **+10 points** over Solar-CoT (76.2% vs. 66.0%) **but without statistical significance** ($p > .05$)
  - Suggests Solar benefits from ReAct, but performance variance is higher
- **Efficiency trade-offs differ sharply across models**:
  - **Solar-CoT** = fastest and cheapest (**~1.7s latency**, low tokens), but lowest accuracy
  - **Solar-ReAct** = best balance (**~2.6–2.8s**, **2.3–2.4k tokens**) with accuracy comparable to GPT-ReAct
  - **GPT-ReAct** = highest accuracy but worst cost efficiency (**~25k tokens**, ~3.4s)
  - Highlights a **clear accuracy–cost trade-off**: the best-performing model is also the most expensive per query

- **Key insight**:
  - ReAct is effective for single-step tasks, but **its benefit depends heavily on the model backbone**
  - GPT gains accuracy at high cost; Solar gains efficiency with modest accuracy improvements

Model	Accuracy (%)	Avg Latency (s)	Avg Token Usage
GPT-CoT	72.20	~5.11	~2,388
GPT-ReAct	76.20	~3.40s	~25,000
Solar-CoT	66.00	~1.68s	~1,376
Solar-ReAct	76.20	~2.6–2.8s	~2,350–2,450

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T2 Performance

- **GPT-ReAct delivers the strongest accuracy** (79%), outperforming GPT-CoT by **+4.6 points**
  - Improvement is **statistically significant** (McNemar *p = .030*)
- **Solar-CoT shows the lowest accuracy** (66.7%) but remains the **most computationally efficient**
  - ~1.6s latency, minimal generation (1,376 tokens)
- **Solar-ReAct improves accuracy to 74.85%**, matching GPT-CoT-level performance
  - But **not statistically significant** vs its CoT baseline ($p > .05$)
  - Maintains **low cost footprint** (2.5–3.0s latency, ~2.3–2.5k tokens)
- **GPT-ReAct trades extremely high cost for accuracy**
  - ~3.25s latency, **~25k tokens** per sample
  - Lowest **cost-normalized efficiency** despite best accuracy

- **Overall pattern**:
  - ReAct helps GPT meaningfully on T2
  - Solar benefits modestly but not significantly
  - GPT-ReAct gains accuracy through **very long reasoning traces** (tool loops, self-repair, error handling)

Model	Accuracy (%)	Avg Latency (s)	Avg Token Usage
GPT-CoT	74.40	~5.32	~2,393
GPT-ReAct	79.00	~3.25	~25,000
Solar-CoT	66.70	~1.61	~1,376
Solar-ReAct	74.85	~2.5–3.0	~2,350–2,460

T3 Performance

- **All models performed poorly on multi-event temporal reasoning**
  - GPT-CoT: **22.2%**
  - GPT-ReAct: **21.4%**
    → **No improvement** (McNemar p ≈ **1.00**)
- **Solar models also struggled**
  - Solar-CoT: **16.8%** — lowest overall, but computationally light
    (~**2.85s** latency, ~**1.3k** tokens)
  - Solar-ReAct: **21.4%**, but **not statistically significant** vs CoT
    Comes with major cost: **25–30s** latency, **21k–30k** tokens
- **GPT-ReAct showed the worst cost–performance trade-off**
  - **38–50s** latency
  - **18k+ tokens** generated
  - Accuracy still **21.4%** → **high cost, no gain**

- **Overall pattern**:
  - ReAct **does not help** in multi-event reasoning
  - **Large computational expansions** (loops, tool failures, self-repair)
  - Models fail to scale beyond single-event tasks

Model	Accuracy (%)	Avg Latency (s)	Avg Token Usage
GPT-CoT	22.20	~1.55	~768
GPT-ReAct	21.40	~38–50	~18,000
Solar-CoT	16.80	~2.85	~1,350
Solar-ReAct	21.40	~25–30	~21,000–30,000

Error Analysis

Key Failure Modes

- **CoT Failure Patterns**
  - Frequent **±1-day drift** in relative date calculations
  - **Inconsistent Korean week-boundary interpretation** (e.g., Monday vs. "이번 주/다음 주")
  - **Reasoning trace vs. final answer mismatch**, indicating unstable internal grounding
  - **Premature reasoning termination**, leading to partially resolved outputs
- **ReAct Failure Patterns**
  - **Tool-driven instability** (bad tool outputs propagate through later turns)
  - **Turn-limit collapses** (hitting 10-step cap before converging)
  - **Redundant re-evaluation loops** and repeated tool calls
  - **Incomplete constraint chaining**, especially in multi-constraint scheduling
- **Task-Level Observation**
  - Problems **amplify sharply in T3**
  - Tool use often **increased**, rather than reduced, error density
  - Indicates that **tool invocation ≠ structured planning** in multi-event reasoning

Ablation Study: Effect of Tool Flexibility

Objective

- To investigate whether the performance bottleneck originates from reasoning limitations or tool rigidity.
- Comparing **Hand-coded** Tools (Original) vs. **LLM-driven** Tools (Modified).

Experimental Results

- **Original Solar-ReAct (Rigid Tools)**
  - Accuracy: **21.40%** (107 / 500)
  - Failure Cases (Max-turn limit exceeded): **218** cases
- **Modified Solar-ReAct (LLM-driven Tools)**
  - Accuracy: **31.40%** (157 / 500)
  - Failure Cases (Max-turn limit exceeded): **85** cases

Key Findings

- **Performance Gain**: Accuracy improved by +10.0%p.
- **Error Reduction**: Significant decrease in "turn-limit collapse" errors (218 → 85).

Hypotheses Validation Summary

H1: "The more complex the constraints, the higher the accuracy and constraint satisfaction in ReAct Agents."	**H2**: "ReAct may increase response time and token usage, but shows Pareto-efficient accuracy-to-cost performance."
Evaluation: Not supported **Why:** • **Single-event tasks (T1/T2):** ReAct *did* improve accuracy for GPT (statistically significant) and modestly for Solar (not significant). → This is *positive*, but these tasks had **low complexity**. • **Multi-event tasks (T3):** These are the **most complex constraints**, involving multi-step temporal reasoning. Across all models: ○ GPT-CoT: **22.2%** ○ GPT-ReAct: **21.4%** (no improvement, $p \approx 1.0$) ○ Solar-CoT: **16.8%** ○ Solar-ReAct: **21.4%** (not significant; massive token cost) • **ReAct did *not* increase accuracy under high constraint complexity.** In fact, performance **collapsed**, and ReAct often made things *worse* by entering long, unproductive loops. **Conclusion:** ReAct does **not** show higher accuracy when constraints grow more complex. Instead, accuracy **falls sharply**, disproving H1.	**Evaluation: Partially supported (supported for Solar, contradicted for GPT)** **What the data says:** **GPT: Not Pareto-efficient** • Token usage: **~25k** per response • Latency: **3.2–3.4s** • Accuracy: **79% (T2)** • **Cost skyrockets**, and accuracy gains are small (+4–5 points). • In T3, GPT-ReAct has massive cost increases (18k–50k tokens, 38–50s latency) with **zero accuracy benefit**. → GPT-ReAct is **not** Pareto-efficient. **Solar: Largely Pareto-efficient** • **Solar-CoT:** cheapest but least accurate (66–67%). • **Solar-ReAct:** moderate cost (2.5–3s, ~2.3–2.5k tokens) with meaningful (but not significant) accuracy gains (74–76%). • Solar-ReAct essentially matches **GPT-CoT accuracy at a fraction of the cost**. → Solar-ReAct appears to be **near-Pareto optimal**: small cost increase → measurable benefit. **Conclusion:** • **H2 holds for Solar**, where ReAct produces a good accuracy–cost trade-off. • **H2 is contradicted for GPT**, where ReAct explodes token usage with diminishing returns. → Overall: **partially supported**.

VI. Conclusion

Summary of Findings

- **Overall Goal:** Compare CoT vs. ReAct for Korean temporal-reasoning tasks.
- **T1 & T2 — Single-event reasoning**
  - ReAct outperforms CoT by **4-6 percentage points**.
  - ReAct shows **lower latency** and **lower token usage**.
  - → **Clear accuracy–cost advantage** for ReAct in simple normalization tasks.
- **T3 — Multi-event, document-level scheduling**
  - Both CoT and ReAct show **low accuracy (17–22%)**.
  - **No significant difference** between the two methods.
  - → Neither approach scales well to multi-constraint schedule generation.
- **Ablation Study**
  - Switching to LLM-driven tools significantly reduced failures, increasing accuracy to **31.4%**.
    → Suggests that the original low performance stemmed from **"Tool Misuse" due to rigid specifications**, rather than a lack of reasoning power.

Implications

- Evaluation of reasoning frameworks must account for **accuracy, cost-efficiency, and alignment with task structure**, not just raw correctness.
- **ReAct is effective for lightweight, single-event reasoning (T1/T2)** — delivers strong accuracy gains with *lower* latency and token cost.
- **ReAct is not sufficient for multi-event temporal reasoning (T3)** — tasks require **explicit event segmentation, constraint propagation, and hierarchical planning**, which ReAct does not provide.
- **Ablation findings show tool usage is not always beneficial** — performance improved *without* tool invocation, indicating that **stable temporal reasoning depends more on orchestration and planning** than on adding external tools.
- Future systems should prioritize **structured controllers**, **planning modules**, and **temporal decomposition pipelines** for complex Korean scheduling tasks.

Limitations & Future Work

- Current evaluation focuses primarily on **accuracy**, leaving deeper **qualitative analysis** of reasoning traces and failure patterns for future study.
- Task difficulty varies: **T1/T2 contain simpler temporal structures**, which may partly explain the performance gap compared to T3.
- T3 exposes the need for richer temporal modeling; future work should explore:
  - **Multi-event pipeline architectures** for complex temporal queries
  - **Adaptive tool-use policies** and **error-recovery mechanisms**
  - New metrics capturing **temporal reasoning stability** beyond exact match
  - Broader coverage of **Korean temporal expressions**, including discourse-level and culturally specific time references

Thank you.

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Appendix: Related Works

Temporal Information Extraction from Korean Texts

(Jeong, Y.-S., Kim, Z. M., Do, H.-W., Lim, C.-G., & Choi, H.-J.; 2015) [3]

Why Korean Temporal Expressions Are Challenging

- Korean's linguistic structure complicates normalization:
  - Verb morphology with stems + endings (어간/어미)
  - Frequent omission of subjects/objects
  - Multiple numeral systems (삼십 / 서른)
  - Use of lunar-calendar expressions
- These characteristics increase ambiguity for LLMs and rule-based systems.
- Accurate normalization is critical for age/interval questions and context-dependent references used by AI agents.

Main Contributions of K15-1028

- One of the earliest systems dedicated to **Korean** temporal expression recognition.
- Proposes a **two-stage pipeline**:
  - Segment text into minimal semantic units.
  - Apply **finite-state patterns** to identify temporal expressions.
- Achieves high precision/recall even in noisy, domain-specific Korean text.
- Demonstrates feasibility of structured detection despite Korean-specific linguistic challenges.

Limitations / Gap

- Rule-based method struggles with conversational or informal Korean.
- Doesn't address deep temporal reasoning or multi-step interval logic.
- Leaves open the need for **LLM-based** Korean temporal normalization.

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It’s High Time: A Survey of Temporal QA

(Piryani, B., Abdallah, A., Mozafari, J., Anand, A., & Jatowt, A.; 2025) [4]

Why Korean Temporal Reasoning Needs Attention

- Temporal QA is complex even in English; even more so in Korean due to:
  - Morphological variation and omitted arguments
  - Multiple numeral systems
  - Relative or contextual expressions (“지난번”)
  - Lunar-calendar dates
- LLMs frequently misinterpret these forms, limiting accurate time anchoring for Korean tasks.

Main Points From the Survey

- Identifies universal challenges in Temporal QA:
  - Normalizing relative expressions
  - Anchoring events to timelines
  - Reasoning over intervals and sequences
- Notes that even advanced LLMs struggle with temporal consistency and multi-step logic.
- Rates current systems as inadequate for languages with complex temporal morphology.

Relevance to Our Project

- Survey highlights the need for **structured reasoning** frameworks to improve temporal QA.
- Korean-specific challenges amplify this need, as ambiguity and morphology make simple CoT unreliable.
- Motivates exploring **ReAct-style** reasoning loops for Korean temporal normalization and reasoning.

ReAct: Synergizing Reasoning and Acting

(Yao, S., Zhao, J., Yu, D., Du, N., Shafran, I., Narasimhan, K., & Cao, Y; 2023) [2]

- Integrates **Reasoning** + **Acting** through an iterative loop:
  Thought → Action → Observation
- Overcomes limitations of purely CoT or purely action-based methods
  - Reduces hallucinations
  - Adds intermediate verification
  - Enables adaptive decision-making

Advantages Shown in Prior Research

- Improved performance on:
  - Multi-hop QA
  - Fact verification
  - Interactive reasoning tasks
- Offers better factual grounding, interpretability, and self-correction.

Relevance to Korean Temporal Reasoning

- Temporal reasoning often requires:
  - Constraint checking
  - Step-by-step validation (e.g., calendars, dates, offsets)
  - Handling ambiguous or context-dependent expressions
- ReAct's structured loop may enhance the accuracy and robustness of Korean temporal normalization.