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Manufacturing process quality prediction via temporal knowledge graph reasoning with adaptive multi-scale temporal path fusion and self-attention mechanism

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A B S T R A C T

To tackle the pronounced temporal dynamics and intricate interdependencies within process manufacturing knowledge, this paper introduces an innovative framework: the Adaptive Multi-Scale Temporal Path Fusion Network (AMTPFNet). The method constructs short-term (high-frequency) and long-term (low-frequency) historical subgraphs to generate multi-scale temporal representations. It also employs a self-attention mechanism for query-aware temporal path modeling, enabling adaptive weight allocation based on varying time spans. Extensive experiments are conducted on benchmark datasets, including ICEWS18, GDELT, WIKI, and YAGO. Additionally, an application analysis is presented using electromechanical fault data. The results demonstrate that AMTPFNet exhibits remarkable effectiveness and robustness in temporal knowledge graph reasoning tasks, achieving MRR scores of 0.914 on YAGO and 0.838 on WIKI. It achieves high efficiency in predicting future production facts and assessing process quality in industrial workflows. Root causes of failures (e.g., insulation, friction) for motor components (stators, rotors) are accurately predicted, demonstrating the framework's transferability to real-world manufacturing scenarios. Although electromechanical fault data are used as a case study, the framework generalizes to manufacturing quality prediction and is readily transferable to finance, healthcare, and social media analytics.

A R T I C L E   I N F O

Keywords:
Temporal knowledge graph reasoning (TKGR);
Multi-scale temporal modeling;
Temporal path fusion;
Self-attention mechanism;
Knowledge graph embedding;
Manufacturing process analytics;
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Izvirni znanstveni članek

Napovedovanje kakovosti proizvodnih procesov z uporabo časovnih grafov znanja, adaptivnega večnivojskega združevanja časovnih poti in mehanizma samopozornosti

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POVZETEK

V prispevku je predstavljen inovativen pristop za obravnavo izrazite časovne dinamike in zapletenih medsebojnih odvisnosti v znanju o proizvodnih procesih – prilagodljiva večnivosjka mreža za združevanje časovnih poti (Adaptive Multi-Scale Temporal Path Fusion Network, AMTPFNet). Pristop temelji na oblikovanju kratkoročnih (visokofrekvenčnih) in dolgoročnih (nizkofrekvenčnih) zgodovinskih podgrafov časovnega grafa znanja za tvorbo večnivojskih časovnih predstavitev. Poleg tega uporablja mehanizem samopozornosti za modeliranje časovnih poti, prilagojenih poizvedbi, kar omogoča adaptivno dodeljevanje uteži posameznim časovnim potem glede na njihovo časovno oddaljenost. Obsežni eksperimenti so bili izvedeni na referenčnih podatkovnih zbirkah ICEWS18, GDELT, WIKI in YAGO. Predstavljena je tudi analiza uporabe na podatkih o elektromehanskih okvarah elektromotorjev. Rezultati kažejo, da AMTPFNet izkazuje visoko učinkovitost in robustnost pri nalogah sklepanja v časovnih grafih znanja, pri čemer dosega MRR 0,914 na podatkovni zbirki YAGO in 0,838 na WIKI. Pri napovedovanju prihodnjih proizvodnih dogodkov ter ocenjevanju kakovosti procesov v industrijskih okoljih se izkaže tudi njegova praktična uporabnost. Temeljni vzroki okvar (npr. izolacija, trenje) pri sestavnih delih elektromotorjev (statorji, rotorji) so natančno napovedani, kar potrjuje prenosljivost pristopa v proizvodna okolja. Čeprav študija primera temelji na podatkih o elektromehanskih okvarah, je pristop splošno uporaben za napovedovanje kakovosti v proizvodnji ter prenosljiv tudi na področja financ, zdravstva in analitike družbenih medijev.

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Ključne besede:
Sklepanje na podlagi časovnih grafov znanja;
Večnivojsko časovno modeliranje;
Združevanje časovnih poti;
Mehanizem samopozornosti;
Vdelava grafov znanja;
Analitika proizvodnih procesov;
Napovedovanje kakovosti procesa

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