Sequential CNN

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Deep Learning Predicts Lung Cancer Treatment Response from Serial Medical Imaging

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Abstract

- Motivation
  - Non-small cell lung cancer (NSCLC)，晚期患者5年生存率仅为18%
  - 晚期一般使用非手术方案，需要对病变发展以及治疗效果进行跟踪
  - 受到血管及免疫系统影响，病变具有明显的动态特征
- Contribution
  - CNN + RNN 预测NSCLC晚期患者的生存率以及治疗效果

Serial Medical Imaging

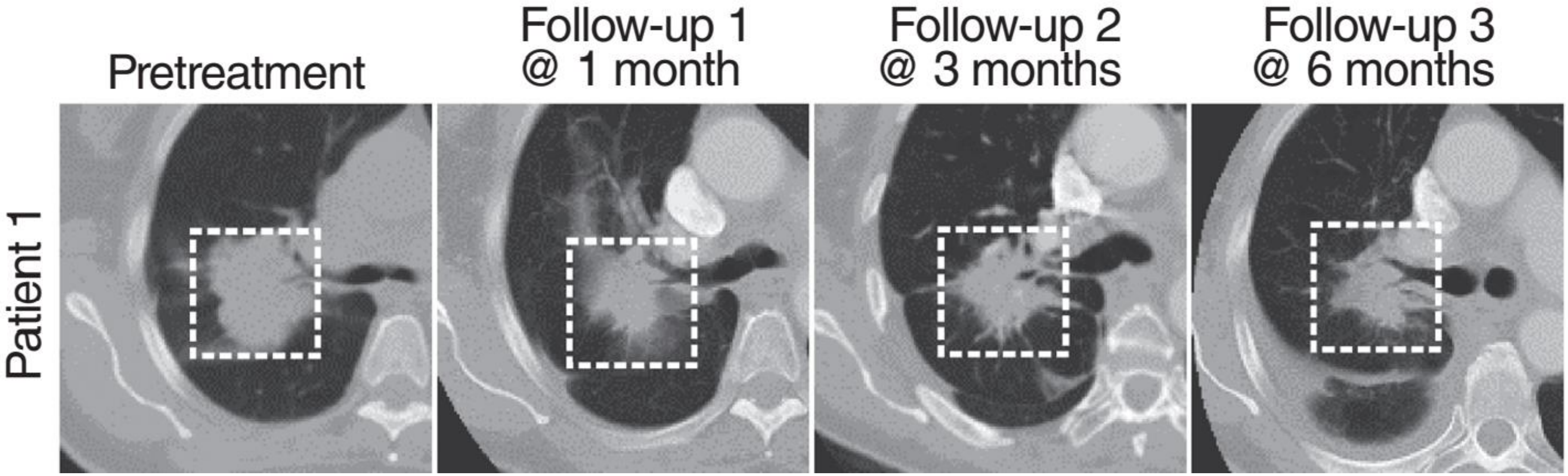
- Dataset-A
  - 179 patients with stage III NSCLC, 2003 – 2014
  - 使用放疗、化疗方案
  - 治疗前1期CT + 治疗1、3、6月后的CT，会有缺失（平均3.2期）
  - 排除在治疗前或治疗后有手术史的病例
  - 107 for training/tuning, 72 for test
  - 评估指标，放化疗1、2年后
    - 生存与否
    - 远处转移
    - 局部复发
    - 进展

Serial Medical Imaging

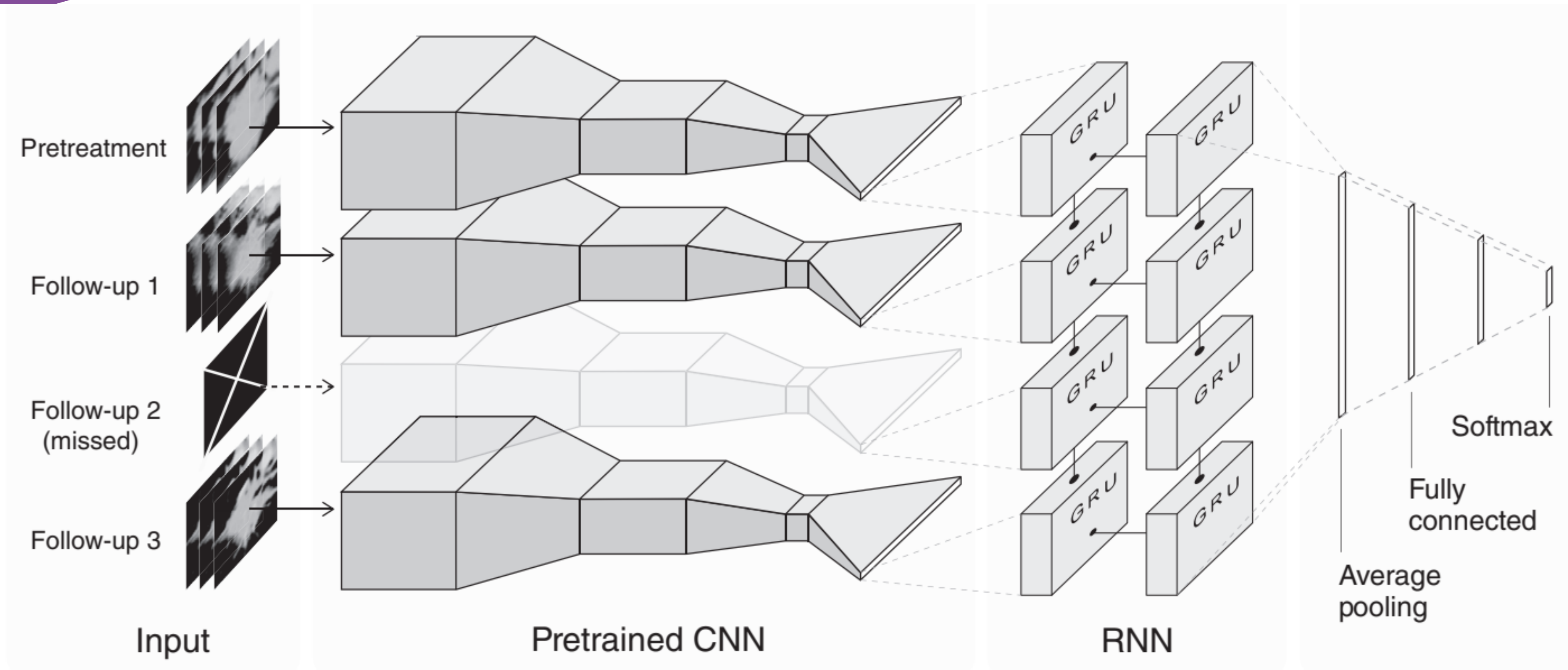
- Dataset-B (additional test)
  - 89 patients with stage III NSCLC, 2001 – 2013
  - 使用术前辅助放疗、化疗方案
  - 每个病人两期图像：治疗前、治疗后
  - 排除病例
    - 远端转移
    - 放化疗与手术间隔大于120天
    - 没有生存数据
  - 评估指标，放化疗后1年
    - 手术时的病情诊断（14个完全缓解，28个支气管癌变，47个残留病变）

Serial Medical Imaging

- 病变区域
  - 人工定位病变位置，点击获取病变中心点
  - 截取上下5mm处共3张切片，$50 \times 50\ mm^2$ 大小



Serial Medical Imaging



1. Imagenet 预训练网络参数，迁移学习
2. 缺失数据跳过

Serial Medical Imaging

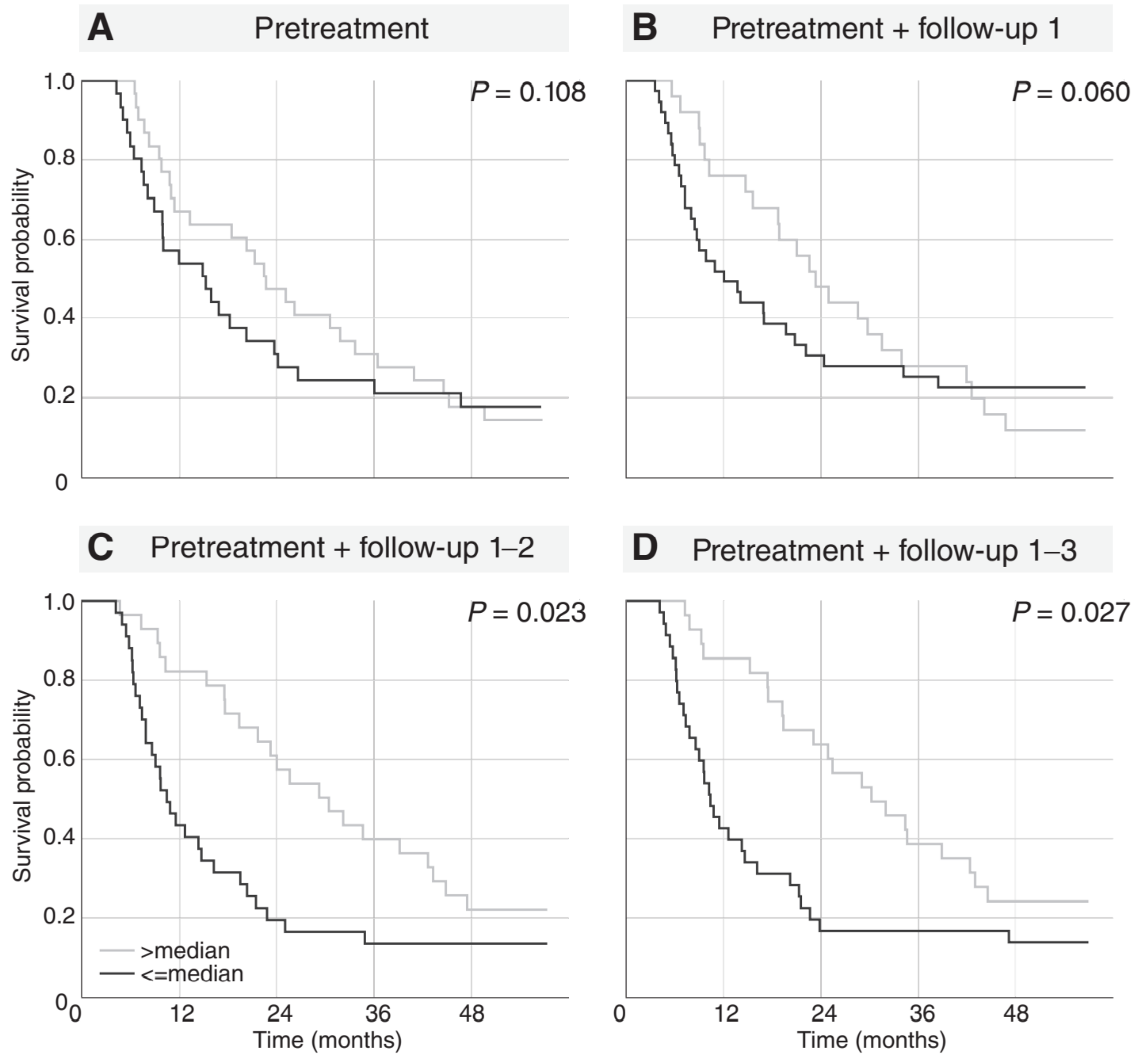
- Baseline
  - 使用RF进行预测
    - 肿瘤分期、性别、年龄、病变分级、吸烟史、病变体积等

- Results
  - Predicting 2-year survival

	1 pre	1 + 1	1 + 2	1 + 3	RF
AUC	0.58	0.64	0.69	0.74	0.51
P值	0.3	0.04	0.007	0.001	0.93

Serial Medical Imaging

- Results
  - 将低风险与高风险人群分开，分别绘制生存率曲线



ATTAIN: Attention-based Time-Aware LSTM Networks for Disease Progression Modeling

Yuan Zhang, Xi Yang, Julie Ivy and Min Chi

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2. Industrial and System Engineering, North Carolina State University

IJCAI, 2019

Abstract

- Motivation
  - 使用 Electronic Health Records (EHRs) 预测疾病发展 Disease Progression Modeling (DPM)
  - 数据之间的时间间隔不规则
- Contribution
  - 引入 attention 机制建模时间间隔
- AATAIN network
  - LSTM：越靠近当前时刻的输入对当前的预测影响越大
  - 作者观点
    - 病变发展不仅仅与邻近时刻有关
    - 医生需要查看病情的历史变化，来判断当前病情及未来病情的发展

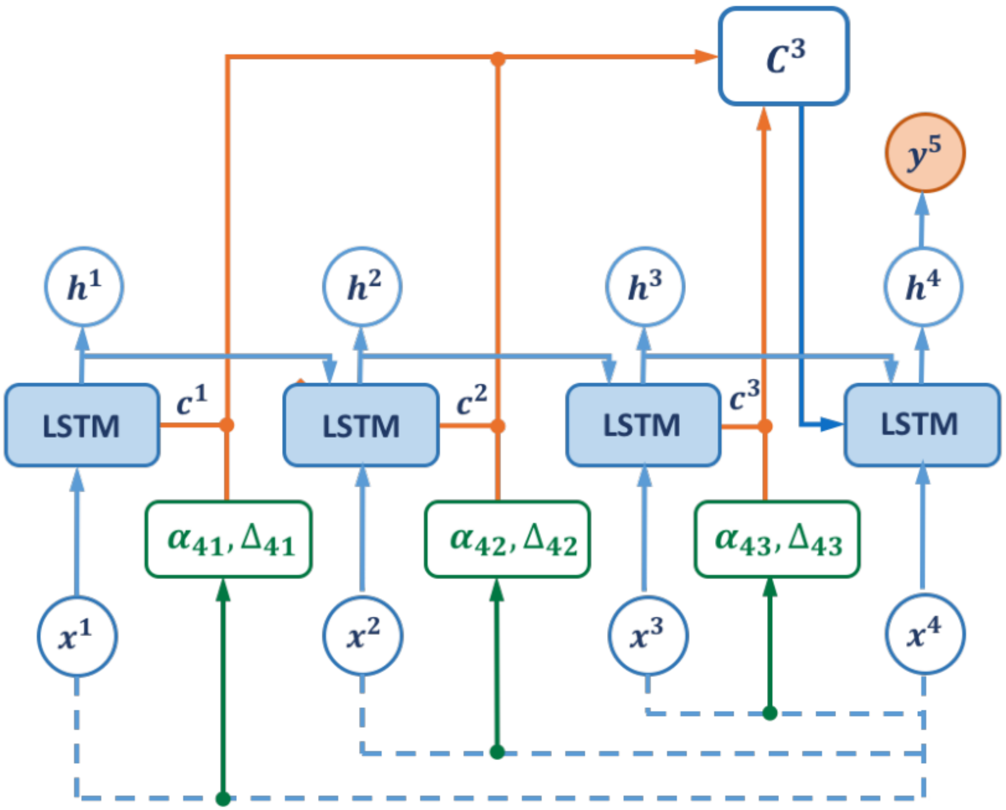
Time-Aware LSTM

- LSTM
  - 信息隐含在“细胞状态C”和“隐状态H”中，缺少对时间间隔的建模

- Attention 机制
  - Global：全部
  - Local：固定数目
  - Flexible：sigmoid attention

- 重要程度随时间衰减

$$g(\Delta t) = 1/\log(e + \Delta t)$$

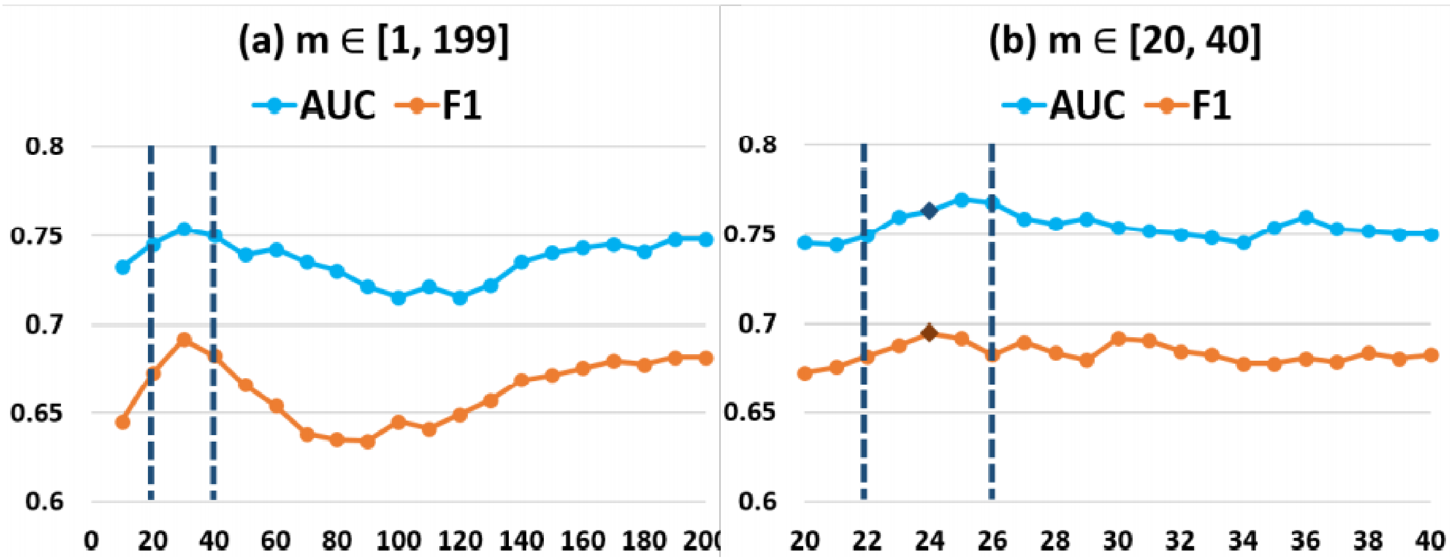


Time-Aware LSTM

- Datasets
  - Christiana Care Health System Health System (CCHS), 2013 – 2015
  - 真菌、细菌、病毒感染，是否发生感染性休克
  - 共 2100 例：1869 正样本 + 231 负样本
  - 共 209346 次记录：22430 正样本 + 186916 负样本

Time-Aware LSTM

- Results
  - Local attention， 选择 m



Time-Aware LSTM

- Results
  - Overall prediction：1, 2, ..., t 预测 t+1

Method	A	T	Sensitivity/Recall	Specificity	PPV/Precision	F1-score	AUC
LSTM	-	-	0.627(±0.023)	0.632(±0.021)	0.635(±0.020)	0.631(±0.021)	0.716(±0.020)
RETAIN	✓	-	0.618(±0.015)	0.654(±0.016)	0.651(±0.016)	0.634(±0.016)	0.732(±0.010)
T-LSTM	-	✓	**0.643**(±0.009)	**0.680**(±0.012)	**0.702**(±0.013)	**0.671**(±0.010)	**0.745**(±0.013)
$LSTM_g$	✓	-	0.628(±0.013)	**0.798**(±0.015)	**0.747**(±0.018)	0.682(±0.016)	0.748(±0.014)
$LSTM_l$	✓	-	**0.684**(±0.007)	0.742(±0.013)	0.707(±0.012)	**0.695**(±0.011)	**0.763**(±0.008)
$LSTM_f$	✓	-	0.667(±0.022)	0.731(±0.017)	0.726(±0.016)	0.695(±0.019)	0.755(±0.016)
$ATTAIN_g$	✓	✓	0.636(±0.016)	⋆ **0.818**(±0.008)	⋆ **0.803**(±0.010)	0.710(±0.014)	0.782(±0.015)
$ATTAIN_l$	✓	✓	⋆ **0.695**(±0.014)	0.746(±0.012)	0.744(±0.015)	0.718(±0.014)	0.804(±0.010)
$ATTAIN_f$	✓	✓	0.686(±0.018)	0.767(±0.016)	0.758(±0.016)	⋆ **0.720**(±0.017)	⋆ **0.811**(±0.011)

- RETAIN：NIPS 2016，从 LSTM 的隐状态中计算 attention 权重
- T-LSTM：ACM 2017，引入时间衰减作为门控

Time-Aware LSTM

- Results
  - Early prediction：1, 2, …, t 预测 t+1, t+2, …, t+η

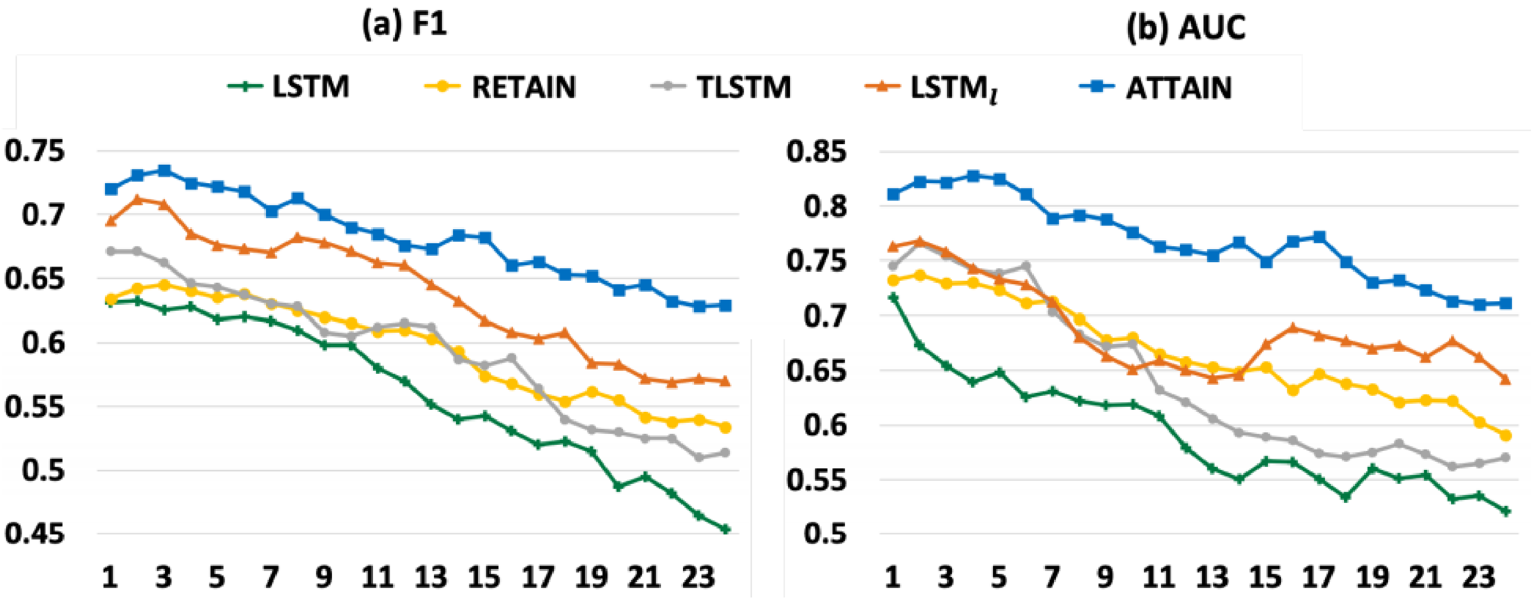
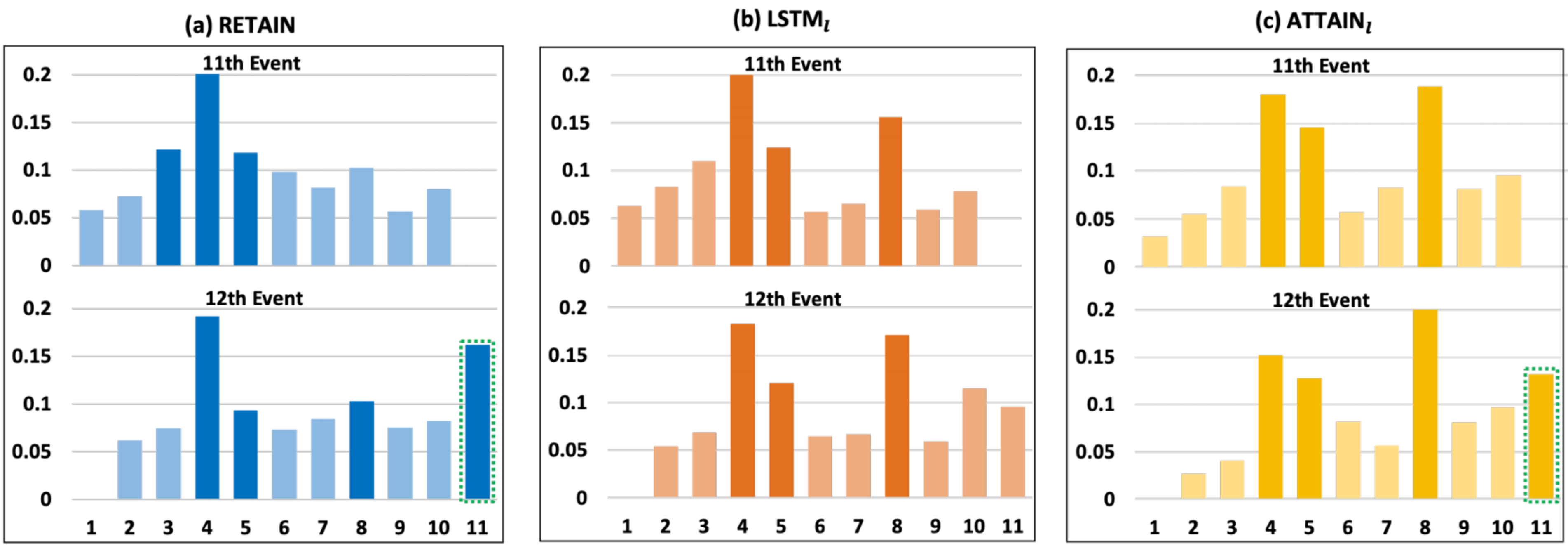


Figure 3: (a) F1-score of early prediction at different hours. (b) AUC of early prediction at different hours.

Time-Aware LSTM

- Results
  - 权重分析
    - 影响相邻时刻预测的权重应该类似



✗ {3,4,5} for E11; {4,5,8} for E12.
✓ E11 is critical for E12.

✓ {4,5,8} for E11; {4,5,8} for E12.
✗ E11 is **not** critical for E12.

✓ {4,5,8} for E11; {4,5,8} for E12.
✓ E11 is critical for E12.

Figure 4: Attention weights for the 11th and 12th events achieved from (a) RETAIN; (b) LSTM$_l$; (c) ATTAIN$_l$.

Time-aware Adversarial Networks for Adapting Disease Progression Modeling

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Abstract

- Motivation
  - 使用 Electronic Health Records (EHRs) 预测疾病发展 Disease Progression Modeling (DPM)
  - 数据之间的不均匀性（异质性）
    - 不同人群下的指标数值分布不同（例如不同年龄人的血压）
    - 不同人群某类观察指标的样本分布不均（例如老年人更易得病）
- Contribution
  - 引入 attention 机制建模时间间隔

Thanks for listening!