Self-Organizing Cellular Radio Access Network with Deep Learning

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Problem Statement

RAN Performance Problems Prevalent

- *My phone shows 5 signal bars but the connection is so slow!*
- Cannot hear your voice!
- This web page is not loading at all!
- Example root causes of RAN performance problems



NOT straightforward to diagnose the root cause!

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| | N | /IN | LA | B | | | | |

Self-Healing Radio Access Network



Can cellular network operators automate the diagnosis and self-healing of RAN?

System challenges:

- How to **predict anomaly KPIs** before any faults really appear?
- How to figure out **root causes** based on thousands of cell KPIs?
- How can the system self recover from the faults?
- How to deal with ~ TB level data of cell KPIs?

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System Overview



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Big Data Platform (Apache Spark + HDFS + Apache HBase)

Spark.

HBASE

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Real-world KPI Dataset Overview

real-word data from a top-tier US cellular operator

- Aggregated Cell Dataset
- KPIs & error code summary: ~100. e.g., mobile subscriber count, attach count, detach count, handover count; x2_attempt, x2_enb_to, x2_dns_fail, s1_intra_src_attempt, s1_intra_tar_sgw_chg, etc,.
- Overall size: ~335 GB
- Collection date: 2017-06-30 2018-03-20
- Collection interval: 1hour
- Non-aggregated Cell dataset
- KPIs summary: ~4k.
- Overall size: ~ 100 TB
- Collection date: 2018-02-01 2018-07-31
- Collection interval: 15 minutes

- Accessibility
- Retainability
- Integrity
- Availability
- Mobility
- Connection Drop Rate
- Cell Throughput

Example KPIs in time series



Partial example KPIs

'InterferencePowerAvg', 'InterferencePowerTot', 'InterferencePowerCnt', 'ThermalNoisePowerAvg', 'ThermalNoisePowerTot', 'ThermalNoisePowerCnt', 'RssiOverPathAvg', 'RssiOverPathTot', 'RssiOverPathCnt', 'RssiPathOAvg'



Anomaly Prediction: Objective & System Challenges

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Objective: based on the currently/historically-reported cell KPIs, to *predict the potential anomaly KPIs/events* in the future

System Challenges:

- Identify related KPIs: Difficult to know in advance which of the thousands of KPIs are relevant and correlated with the predictive KPIs.
- Inter-cell interference: Some KPIs from neighboring cells may be related, like in the case of high intercell interference, but may not trigger an anomaly event at these neighbor cells.
- <u>Rare anomaly events</u>: The anomaly event labels rarely account for less than 0.1 percent over all the reported KPIs. The model needs to focus on those anomaly points.





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Anomaly Detection: Model Selection

CNN



- Good at extracting spatial features from input: which KPIs are more correlated to the predictive target?
- Ignore temporal relations

RNN



- Good at extracting temporal relations between timeseries inputs
- Detect "periodic" pattern
- Selectively remember "important" time slots
- Gradient vanishing & gradient explosion
- Cannot remember long-term information

LSTM (Long Short Term Memory)



- Resolve gradient vanishing & gradient explosion
- Enable long-term memory
- Cannot well extract spatial features



Anomaly Detection: ConvLSTM

• Extracting both *temporal* and *spatial* features



- Input: thousands of historical cell KPIs
- Output: predictive values of target cell KPIs
- Model structures (similar to <u>LSTM</u>)

 $\begin{array}{ll} \textit{input gate} & i_t = \sigma(W_{xi} \ast X_t + W_{hi} \ast H_{t-1} + W_{ci} \circ C_{t-1} + b_i \\ \textit{forget gate} & f_t = \sigma(W_{xf} \ast X_t + W_{hf} \ast H_{t-1} + W_{cf} \circ C_{t-1} + b_f \\ \textit{sigmoid state} & C_t^* = tanh(W_{hc^*} \ast H_{t-1} + W_{xc^*} \ast X_t | + b_f) \\ \textit{update gate} & C_t = f_t \circ C_{t-1} + C_t^* \\ \textit{output gate} & o_t = \sigma(W_{xo} \ast X_t + W_{ho} \ast H_{t-1} + W_{co} \circ C_t + b_o) \\ \textit{hidden state} & H_t = o_t \circ tanh(C_t) \\ \textit{output} & Y_t = W_{hy} \ast H_t + b_{hy} \end{array}$

- The operator "*" (convolution operations) that is the key in this model
- The convolution operation enables to extract spatial features

Xingjian, S. H. I., et al. "Convolutional LSTM network: A machine learning approach for precipitation nowcasting." Advances in neural information processing systems. 2015.

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Anomaly Detection: Unbalanced Dataset

How to handle extremely unbalanced dataset? (Rare anomaly events)

- Data undersampling
 - <u>Discard the redundant data</u> that is far from the the anomaly points.



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- Penalized classification
 - Penalizing error anomaly classification will introduce an extra cost to the model when it falsely classifies an anomaly point as a normal one. These penalties force the model to give greater emphasis to the minority class.

trainLoss = $\alpha * normClass + \beta * anomalyClass(<math>\alpha \ll \beta$)



Root Cause Analysis: System Challenges

System Challenges

- Root cause labels are *not available* for supervised training
 - Network engineers do not deliberately attach the resulting fault to the associated logs
 - Too expensive to collect the logs by purposely introducing the cell faults

Solutions

- Generate a *synthetic dataset* of cell faults with NS3
- Employ unsupervised clustering by removing the fault labels, with which we are able to quantify how the model performs
- Apply the model to a real-world dataset



Root Cause Analysis: NS3 simulation

NS3 simulation steps







power radiation of normal/anomaly eNBs



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NS3 simulation setup

| Parameter | Value | | | | |
|-----------------------|--|--|--|--|--|
| Тороlоду | 3-sector hexagonal grid, 3 sites | | | | |
| Carrier Freq. | 2.12 GHz | | | | |
| Bandwidth | 10 MHz | | | | |
| Channel model | UMi, shadow fading, no fast fading | | | | |
| TX power | 46 dBm | | | | |
| Antenna | 3D parabolic 70° azim., 10° vertical beamwidth 9° downtilt | | | | |
| Handover algorithm | A3 RSRP (default Hyst = 3 dB, TTT = 256 ms) | | | | |
| Scheduler | Proportional fair | | | | |
| Mobility model | Steady state random waypoint UE speeds $\in U(1,20)m/s$ | | | | |
| Traffic model | Constant bit rate 800 kbps DL + UL flows | | | | |

normal cell configuration

- EU: excessive uptilt
- ED: excessive downtilt
- ERP: excessive cell power reduction
- CH: coverage hole
- TLHO: too late handover
- *II: inter-cell interference*

| Fault Cause | Configuration |
|-------------|--|
| EU | Downtilt= $[0,1]^{\circ}$ |
| ED | Downtilt=[16,15,14] ° |
| ERP | $\Delta P_{TX} = [7, 8, 9, 10] \text{ dB}$ |
| CH | $\Delta_{hole} = [49, 50, 52, 53] \text{ dBm}$ |
| TLHO | HOM=[6,7,8] dBm |
| II | $P_{TX_{max}} = 33 \text{ dBm}$ |
| | Downtilt=15 ° |
| | AB=[30, 60] ° |
| | EB=10 $^{\circ}$ |
| No fault | Normal |

fault cell configuration

Root Cause Analysis: NS3 simulation

- 6 possible faults:
 - EU (excessive uptilt),
 - ED (excessive downtilt),
 - ERP(excessive power reduction),
 - *II (inter-cell interference)*
 - TLHO (too late handover)
 - CH (coverage hole)
- Randomly select 6 out of 30 cells as the faulty ones
- Randomly assign 1 possible fault to the faulty cell

• 40 KPIs

'ul_delay_max', 'ul_PduSize_avg', 'dlrx_size', 'dl_TxBytes', 'ulmac_mcs', 'dl_PduSize_std','fault', 'dl_delay_max', 'ul_delay_avg', 'ul_PduSize_min', 'ul_TxBytes', 'dltx_size', 'dl_nRxPDUs','ultx_mcs', 'ulmac_sframe', 'dlrsrp', 'ul_delay_std', 'ul_PduSize_std', 'ul_nTxPDUs', 'dist', 'dl_PdSize_max','ultx_size','dl_delay_std','ul_RxBytes','dl_Pd uSize_min', 'dl_RxBytes','ul_PdSize_max', 'ul_nRxPDUs', 'dlrx_mcs', 'dlsinr', 'dl_delay_avg', 'ulmac_frame', 'dlrx_mode','dl_delay_min', 'ulmac_size', 'dl_PduSize_avg', 'dl_nTxPDUs', 'dltx_mcs', 'ul_delay_min', 'UE location'

1 hour duration

snapshot of the dataset

| | A | B | c | D E | | ` | | | J | К | L | M | N | 0 | P | 0 | R | | | U | |
|----|------------|-----|---------------|------------------------|-----------------|---------------|------|-----------|----------------|-----------------|------------------|----------------|-----------|-------------|---------------|--------------|--------------|---------------|-----------|---------------|-------------------|
| 1 | cellid tir | me | ulmac size | ditxphy msc dirsrp | diric nrxpdus d | diric txbytes | ault | lsinr d | Irlc pdusize o | llsinr | dltxphy size dlr | ic rxbytes dir | mac msc d | diric delav | dirxphy msc d | irxphy se | ulmac msc | ultxphy msc d | lmac size | ultxphy size | interference |
| 2 | 28 | 0.2 | 211.280275106 | 28 2.899803/766792E-13 | 1.5 | 21112 | 3 | 1,889095 | 1056 | 611.3317779407 | 2961 | 1584 | 28 | 0.017 | 28 | 29 51 | 319360351563 | 319360351563 | 2961 | 2111280280118 | 313,0409748262829 |
| 3 | 28 | 0.3 | 211.280275106 | 28 2.8569203042326E-13 | 1.5 | 2112 | 3 | 1.889095 | 1056 | 602.2911990799 | 2961 | 1584 | 28 | 0.017 | 28 | 2951 | 3.9360351563 | 3.9360351563 | 2961 | 211.280280113 | 3 3.0409748262329 |
| 4 | 28 | 0.4 | 175.348144531 | 28 2.8148648131869E-13 | 2.5 | 3168 | 3 | 1.85025 | 1056 | 593.4258915011 | 2961 | 2640 | 28 | 0.017 | 28 | 29 1 | 2.3332519531 | 2.2915039063 | 2961 | 173.946289063 | 3 2.088120565625 |
| 5 | 28 | 0.5 | 229.281593323 | 28 2.7736289445455E-13 | 2.5 | 3168 | 3 | 1.85025 | 1056 | 584.7322978326 | 5 2961 | 2640 | 28 | 0.017 | 28 | 2901 | 3.0364608765 | 3.0364532471 | 2961 | 229.282211304 | 4 1.3605782263672 |
| 6 | 28 | 0.6 | 544.5 | 28 2.7331833467738E-13 | 2.5 | 3168 | 3 | 1.81243 | 1056 | 576.2061803528 | 3 2961 | 2640 | 28 | 0.017 | 28 | 2961 | 10 | 10 | 2961 | 544.5 | 5 2.12151305 |
| 7 | 28 | 0.7 | 172.500686646 | 28 2.6935211078559E-13 | 2 | 2112 | 3 | 1.81243 | 1056 | 567.8442945451 | 2961 | 2112 | 28 | 0.017 | 28 | 296 | 2.0416717529 | 2.0403747559 | 2961 | 172.466217041 | 1 1.8434034068359 |
| 8 | 28 | 0.8 | 228.750343323 | 28 2.6546186797386E-13 | 2 | 2112 | 3 | 1.775615 | 1056 | 559.6430423222 | 2961 | 2112 | 28 | 0.017 | 28 | 296 | 3.0208358765 | 3.0177612305 | 2961 | 228.669250488 | 3 1.719890719043 |
| 9 | 28 | 0.9 | 500.6640625 | 28 2.6164624861111E-13 | 2 | 2112 | 3 | 1.73979 | 1056 | 551.5988026256 | 5 2961 | 2112 | 28 | 0.017 | 28 | 296. | 7.017578125 | 4.0703125 | 2961 | 282.9375 | 5 1.5997480875 |
| 10 | 28 | 1 | 172.500686646 | 28 2.579033346561E-13 | 2.5 | 3168 | 3 | 1.73979 | 1056 | 543.7076770888 | 3 2961 | 2640 | 28 | 0.017 | 28 | 2961 | 2.0416717529 | 2.041683197 | 2961 | 172.50151062 | 2 1.8519879962891 |
| 11 | 28 | 1.1 | 281.5625 | 28 2.5423111241337E-13 | 1.5 | 2112 | 3 | 1.704935 | 1056 | 535.9665369998 | 3 2961 | 1584 | 28 | 0.017 | 28 | 2961 | 4.03125 | 4.0625 | 2961 | 278.125 | 5 1.6256818966797 |
| 12 | 28 | 1.2 | 180.359375 | 28 2.5062855815974E-13 | 1.5 | 2112 | 3 | 1.704935 | 1056 | 528.3720118599 | 2961 | 1584 | 28 | 0.017 | 28 | 2961 | 2.171875 | 2.171875 | 2961 | 180.359375 | j 2.1588516 |
| 13 | 28 | 1.3 | 172.500686646 | 28 2.4709435388072E-13 | 1.5 | 2112 | 3 | 1.67099 | 1056 | 520.9208986281 | 2961 | 1584 | 28 | 0.017 | 28 | 2961 | 2.0416717529 | 2.0416717529 | 2961 | 172.500686646 | 3 1.9013077572266 |
| 14 | 28 | 1.4 | 278.125 | 28 2.4362646455028E-13 | 3.5 | 3168 | 3 | 1.637925 | 1056 | 513.6100497433 | 3 2961 | 3696 | 28 | 0.017 | 28 | 2961 | 4.0625 | 4.125 | 2961 | 271.25 | 5 1.7330785373047 |
| 15 | 28 | 1.5 | 177.27734375 | 28 2.4022384130291E-13 | 3.5 | 3168 | 3 | 1.605705 | 1056 | 506.4361004964 | 2961 | 3696 | 28 | 0.017 | 28 | 2961 | 2.0439453125 | 2.0439453125 | 2961 | 177.27734375 | 5 2.4120340005859 |
| 16 | 28 | 1.6 | 173.563186646 | 28 2.3688440338756E-13 | 3.5 | 3168 | 3 | 1.605705 | 1056 | 499.396744426 | 5 2961 | 3696 | 28 | 0.017 | 28 | 2961 | 2.0729117529 | 2.0677185059 | 2961 | 173.423248291 | 1 1.9709440927734 |
| 17 | 28 | 1.7 | 249.002197266 | 28 2.3360772026846E-13 | 1 | 2112 | 3 | 1.605705 | 528 | 492.4881114437 | 2961 | 1056 | 78 | 0.00 | 28 | 23 61 | ana | rc 4 | 2961 | 249.008789063 | 3 1.4936061804688 |
| 18 | 28 | 1.8 | 172.500686646 | 28 2.303912499183E-13 | 1 | 2112 | 3 | 1.574315 | 528 | 485.707625586 | 5 2961 | 1056 | 28 | 0.0035 | 28 | 2961 | 0 16 1 529 | 2.041 513184 | 2961 | 172.492584229 | 2.1886146304688 |
| 19 | 28 | 1.9 | 213.004394531 | 28 2.2723469321861E-13 | 1 | 2112 | 3 | 1.543715 | 528 | 479.0523798614 | 2961 | 1056 | 28 | 0.0085 | 28 | 2961 | 4 | 4 | 2961 | 213.004394531 | 1 1.4593047875 |
| 20 | 28 | 2 | 277 | 28 2.2413612772892E-13 | 2.5 | 3168 | -3 | 1.543715 | 1056 | 472.5198914674 | 2961 | 2640 | 28 | 0.017 | 28 | 2961 | 8 | 8 | 2961 | 271 | 2.35475825 |
| 21 | 28 | 2.1 | 177.3828125 | 28 2.2109410134026E-13 | 2.5 | 3168 | | 1.51389 | 1056 | 466.1072836535 | 5 2961 | 2640 | 28 | 0.017 | 28 | 2961 | 2.0454101563 | 2.0454101563 | 2961 | 177.3828125 | 5 2.2642017511719 |
| 22 | 28 | 2.2 | 276 | 28 2.1810821180586E-13 | 1 | 2112 | 3 | 1.484815 | 528 | 459.8121322435 | 5 2961 | 1056 | 28 | 0.0085 | 28 | 2961 | 4 | 4 | 2961 | 261 | / 1.5133929707031 |
| 23 | 28 | 2.3 | 595.561035156 | 28 2.1517664599613E-13 | 1 | 2112 | 3 | 484815 | 528 | 453.6315027526 | 5 2961 | 1056 | 28 | 0.0085 | 28 | 2961 | 8.255859375 | 5.0234375 | 2961 | 375.423828125 | 5 1.5440763496094 |
| 24 | 28 | 2.4 | 256.875171661 | 28 2.1229788277127E-13 | 3.5 | 3168 | 3 | 1.5647 | 1056 | 447.5633974619 | 2961 | 3696 | 28 | 0.0135 | 28 | 2961 | 3.5104179382 | 2.0416946411 | 2961 | 172.502334595 | 5 2.2436435478516 |
| 25 | 28 | 2.5 | 500.328125 | 28 2.0947163264719E-13 | 3.5 | 3168 | 3 | 1.45017 | 1056 | 441.604936517 | 2961 | 3696 | 28 | 0.0135 | 28 | 2961 | 7.03515625 | 7.0234375 | 2961 | 499.84375 | 5 1.4341564546875 |
| 26 | 28 | 2.6 | 172.500686646 | 28 2.0669628902132E-13 | 3.5 | 3168 | 3 | 1.42883 | 1056 | 435.7536614367 | 2961 | 3696 | 28 | 0.0135 | 28 | 2961 | 2.0416717529 | 2.020690918 | 2961 | 171.938049316 | 3 1.63610431875 |
| 27 | 28 | 2.7 | 500.9375 | 28 2.039705994751E-13 | 3.5 | 2112 | 3 | 1.40187 | 1056 | 430.0075872778 | 3 2961 | 3696 | 28 | 0.01116665 | 28 | 2961 | 7.03125 | 7.25 | 2961 | 500.5 | 5 1.3046641171875 |
| 28 | 28 | 2.8 | 177.48828125 | 28 2.0129352300666E-13 | 3.5 | 2112 | 3 | 1.40187 | 1056 | 424.3643094692 | 2961 | 3696 | 28 | 0.01116665 | 28 | 2961 | 2.046875 | 2.03125 | 2961 | 177.3359375 | j 2.0875824804688 |
| 29 | 28 | 2.9 | 256.875171661 | 28 1.9866455834145E-13 | 2 | 3168 | 3 | 1.375575 | 156 | 18.8210000756 | 2961 | 2112 | 28 | 0.017 | 28 | 2961 | 3.5104179382 | 3.0178833008 | 2961 | 228.670349121 | 1.7248147191406 |
| 30 | 28 | 3 | 392.328125 | 28 1.9608184173229E-13 | 2 | 3168 | 3 | 1.349925 | 1 1 56 | 113.3767614421 | 9 1 | 2112 | 28 | 0.017 | 28 | 2961 | 5.53515625 | 4.1875 | 2961 | 288.25 | i 1.5662938 |
| 31 | 28 | 3.1 | 140.683636665 | 28 1.935452443142E-13 | 2 | 3168 | 3 | 1.349925 | 1 56 | 408 02 89 89 21 | 911 | 2112 | 28 | 0.017 | 28 | 2961 | 3.98828125 | 3.98828125 | 2961 | 140.683765411 | 1 1.8942802887695 |
| 32 | 28 | 3.2 | 187.966818333 | 28 1.9105287787585E-13 | 2 | 2112 | 3 | 1.324895 | 1056 | 402.77475063 | 3 2961 | 2112 | 28 | 0.017 | 28 | 2961 | 2.556640625 | 2.48828125 | 2961 | 185.683765411 | 1.407280749585 |
| 33 | 28 | 3.3 | 258.359375 | 28 1.8860444497562E-13 | 2 | 2112 | 3 | 1.324895 | 1056 | 397.6130900824 | 2961 | 2112 | 28 | 0.017 | 28 | 2961 | 5.33203125 | 5.33203125 | 2961 | 258.359375 | j 1.570740515625 |
| 34 | 28 | 3.4 | 175.070333958 | 28 1.8619904735234E-13 | 3 | 3168 | 3 | 1.30047 | 1056 | 392.5414563252 | 2961 | 3168 | 28 | 0.01465 | 28 | 2961 | 2.1328125 | 2.265625 | 2961 | 173.140625 | j 1.5880388526367 |
| 35 | 28 | 3.5 | 381.026367188 | 28 1.8383495819488E-13 | 3 | 3168 | 3 | 1.2766315 | 1056 | 387.5583986734 | 2961 | 3168 | 28 | 0.01465 | 28 | 2961 | 5.1357421875 | 2.5234375 | 2961 | 200.5859375 | i 1.5548901625 |
| 36 | 28 | 3.6 | 230.373046875 | 28 1.8151243333553E-13 | 3 | 3168 | 3 | 1.2533675 | 1056 | 382.6616137304 | 2961 | 3168 | 28 | 0.01465 | 28 | 2961 | 3.064453125 | 3.03515625 | 2961 | 229.58984375 | j 2.2576297851563 |
| 37 | 28 | 3.7 | 253.474630833 | 28 1.792296776476E-13 | 3 | 2112 | 3 | 1.2533675 | 1056 | 377.849552859 | 2961 | 3168 | 28 | 0.0144 | 28 | 2961 | 3.748046875 | 2.96875 | 2961 | 158.157623291 | 1 2.0180640430664 |
| 38 | 28 | 3.8 | 401.686523438 | 28 1.769863534376E-13 | 3 | 2112 | 3 | 1.230647 | 1056 | 373.11991369 | 2961 | 3168 | 28 | 0.0144 | 28 | 2961 | 5.5322265625 | 5.53125 | 2961 | 401.616210938 | 3 1.5496058597656 |
| 39 | 28 | 3.9 | 253.420909166 | 28 1.7478132433863E-13 | 4 | 3168 | 3 | 1.208472 | 1056 | 368.4716718622 | 2 2961 | 4224 | 28 | 0.0135 | 28 | 2961 | 3.7470703125 | 2.984375 | 2961 | 158.578296661 | 1 2.1084995529297 |
| 40 | 28 | 4 | 176.547046661 | 28 1.7261423334147E-13 | 4 | 3168 | 3 | 1.208472 | 1056 | 363.9027777572 | 2 2961 | 4224 | 28 | 0.0135 | 28 | 2961 | 2.359375 | 2.3593826294 | 2961 | 176.547973633 | 3 1.9678409675781 |
| 41 | 28 | 4.1 | 246.687911987 | 28 1.7048381111073E-13 | 4 | 3168 | 3 | 1.208472 | 1056 | 359.4115502446 | 5 2961 | 4224 | 28 | 0.0135 | 28 | 2961 | 7.1041564941 | 5.9633789063 | 2961 | 208.033203125 | i 1.5661931179688 |
| 42 | 28 | 4.2 | 176.638183594 | 28 1.683894550327E-13 | 1 | 2112 | 3 | 1.1868085 | 528 | 354.9959777417 | 2961 | 1056 | 28 | 0.0085 | 28 | 2961 | 2.0314941406 | 2.0307617188 | 2961 | 176.662109375 | i 1.95710145625 |
| 43 | 28 | 4.3 | 230.897888184 | 28 1.6633029996551E-13 | 1 | 2112 | 3 | 1.1656585 | 528 | 350.6553385273 | 3 2961 | 1056 | 28 | 0.0085 | 28 | 2961 | 3.0078125 | 2.02734375 | 2961 | 176.525390625 | i 1.8841027421875 |
| 44 | 28 | 4.4 | 301.296875 | 28 1.6430614226292E-13 | 1.5 | 3168 | 3 | 1.1449935 | 528 | 346.3880277586 | 5 2961 | 1584 | 28 | 0.0085 | 28 | 2961 | 4.74609375 | 4.734375 | 2961 | 301.03125 | j 1.910369490625 |
| 45 | 28 | 4.5 | 160.481284231 | 28 1.6231572804243E-13 | 1.5 | 3168 | 3 | 1.1449935 | 528 | 342.1911489597 | 2961 | 1584 | 28 | 0.0085 | 28 | 2961 | 1.5616862178 | 1.1217398643 | 2961 | 143.925046444 | 4 1.5422658097412 |
| 46 | 28 | 4.6 | 422.230407715 | 28 1.6035842694496E-13 | 1.5 | 3168 | 3 | 1.1248055 | 528 | 338.064811133 | 3 2961 | 1584 | 28 | 0.0085 | 28 | 2961 | 5.8770141602 | 5.5073242188 | 2961 | 401.952636719 | J 1.3106922876953 |
| 47 | 28 | 4.7 | 160.050048828 | 28 1.5843343610298E-13 | 1 | 2112 | 3 | 1.0872415 | 528 | 334.0070315995 | 5 2961 | 1056 | 28 | 0.0085 | 28 | 2961 | 1.5053710938 | 1.5048828125 | 2961 | 160.045410156 | j 1.8839077010742 |
| 48 | 28 | 4.8 | 166.605879009 | 28 1.5654052013886E-13 | 1 | 2112 | 3 | 1.0872415 | 528 | 330.0164867548 | 3 2961 | 1056 | 28 | 0.0085 | 28 | 2961 | 2.4400228262 | 3.0099277496 | 2961 | 160.170810699 | J 1.6727647943359 |
| 49 | 28 | 4.9 | 109.627197266 | 28 1.5467850013022E-13 | 1 | 3168 | 3 | 1.0679795 | 528 | 326.0910663235 | 5 2961 | 1056 | 28 | 0.0085 | 28 | 2961 | 0.0416259766 | 0.0825195313 | 2961 | 110.278320313 | 3 1.7393347814453 |
| 50 | 28 | 5 | 160.293379009 | 28 1.5284728611125E-13 | 1 | 3168 | 3 | 1.0679795 | 528 | 322.230964264 | 2961 | 1056 | 28 | 0.0085 | 28 | 2961 | 1.5201009512 | 0.0669403076 | 2961 | 109.782688141 | 1 1.5691462202393 |
| 51 | 28 | 5.1 | 220.578125 | 28 1.510460888991E-13 | 1 | 3168 | 3 | 1.0384465 | 528 | 318.4332417568 | 3 2961 | 1056 | 28 | 0.0085 | 28 | 2961 | 3.25 | 3.2265625 | 2961 | 220.765625 | i 1.8561719203125 |
| 52 | 28 | 5.2 | 142.895881653 | 28 1.4927404183823E-13 | 1 | 2112 | 3 | 1.0200565 | 528 | 314.6977500599 | 2961 | 1056 | 28 | 0.0085 | 28 | 2961 | 1.0052089691 | 0.0049438477 | 2961 | 108.671264648 | 3 1.6010166367188 |
| 53 | 28 | 5.3 | 381.56710434 | 28 1.4753119670139E-13 | 1 | 2112 | 3 | 1.0200565 | 528 | 311.0224548541 | 2961 | 1056 | 28 | 0.0085 | 28 | 2961 | 5.0944004059 | 2.7550048828 | 2961 | 229.534912109 | 1.352629170401 |
| 54 | 28 | 5.4 | 375 | 28 1.4581576679704E-13 | 1.5 | 3168 | 3 | 1.002083 | 1056 | 307.4067236796 | 2961 | 1584 | 28 | 0.0135 | 28 | 2961 | 6.171875 | 6.15625 | 2961 | 375.625 | 1.544611734375 |
| 55 | 28 | 5.5 | 193.123867393 | 28 1.4412814500662E-13 | 1.5 | 3168 | 2 | 1.002083 | 1056 | 303.8493650639 | 2961 | 1584 | 28 | 0.0135 | 28 | 2961 | 4.0138347149 | 4.0325469971 | 2961 | 192.850517273 | 3 1.5191023734131 |



Root Cause Analysis: Unsupervised Learning

- Feature selections
 - a critical preprocessing step that <u>selects a subset</u> from the <u>high-dimension input</u> to decrease the <u>overfitting</u> probability and to reduce the <u>training/inference</u> time
- Auto-encoder is an unsupervised <u>data</u> <u>coding</u> approach that can extract both linear and nonlinear relations from highdimensional input
 - the similar feed-forward network structure with CNN and consists of two symmetrical components: encoder and decoder
 - The encoder takes the highdimensional data and outputs the lowdimensional one, while the decoder will learn to fully recover the initial input from the compressed output with little loss.



Root Cause Analysis: Unsupervised Learning

- Agglomerative Clustering
 - A bottom-up algorithm.
 - Flow: starts by regarding each feature input as an independent cluster and repeats to merge two nearest clusters (measured by *Euclidean distance* or *Pearson correlation distance*) iteratively until the total remaining cluster number equals to a predefined number.
 - Limitation: <u>cannot</u> naturally map each cluster to a <u>particular fault class.</u> A network expert may further need to empirically infer the physical representation of each cluster, e.g., intercell interference, based on the distributions of significant KPIs.





Evaluations: Anomaly Prediction

- Prediction Objective: used the last 5 hours data to predict the value in the next hour of "<u>X2 handover failure rate</u>" (only an example) (using realworld dataset)
- **Deep Learning Models** (implemented with Tensorflow/Keras):
 - CNN (resnet50)
 - LSTM
 - convLSTM
 - CNN + convLSTM

• Performance Metrics:

- true positive (TP): the number that anomaly points are correctly predicted (key indicator)
- false negative (FN): the number that anomaly points are missing
- false positive (FP): the number that we give a false alarm over a a normal case
- true negative (TN): the number that we correctly predict a normal case
- MSE: mean square error over the anomaly points and the whole dataset

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Evaluations: Anomaly Prediction

Prediction Performance with Different ML Models

| Model | ТР | FP | ANOM_MSE | ALL_MSE | | |
|-------------|----|----|----------|---------|--|--|
| LSTM | 1 | 5 | 0.0185 | 0.0041 | | |
| CNN | 3 | 11 | 0.032 | 0.0083 | | |
| ConvLSTM | 15 | 17 | 0.0117 | 0.0032 | | |
| CNNConvLSTM | 18 | 23 | 0.00096 | 0.0022 | | |

Prediction Performance with Different Anomaly Class Weights

| Weight | ТР | TN | FP | FN | recall |
|----------|----|------|------|----|--------|
| 0.01/1 | 16 | 5854 | 391 | 7 | 69.5% |
| 0.001/1 | 20 | 4442 | 1802 | 3 | 86.9% |
| 0.0001/1 | 23 | 3022 | 3223 | 0 | 100% |

normal weight/anomaly weight

```
recall = TP/(TP+FN)
```

- ConvLSTM, and CNN+convLSTM perform much better than LSTM and CNN
 - Important to extract spatial and temporal features at the same time

- An insufficiently high weight => low recall
- Excessively increase the weight => blindly classify any input as anomaly KPIs
- Needs to explore the trade-off between the anomaly prediction accuracy and the tolerance of false alarms to reach an optimal point.

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Evaluations: Root Cause Analysis

Clustering accuracy: <u>99.5 %</u> by comparing the fault labels in the dataset. (<u>Auto-encoder + agglomerative clustering</u>)



KPI distributions over 6 faulty cases + 1 normal case

• Although the network cluster might be unknown, we can take it as the input to the deep reinforcement learning for the self-healing.

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Conclusions & Future Work

- Propose a <u>self-organizing cellular radio access network system</u> with deep learning
- Design and implement the <u>anomaly prediction</u> and <u>root cause analysis</u> components with deep learning and the evaluation of the system performance with real world data from a top-tier US cellular network operator
- Demonstrate that the proposed methods can achieve <u>86.9%</u> accuracy for anomaly prediction and <u>99.5%</u> accuracy for root cause analysis

Future Work

- Continue to design and implement the last component, "<u>self-healing functions</u>" with <u>deep</u> <u>reinforcement learning</u> and make RAN as an integrated, close-loop, self-organizing system.
- Investigate the root cause analysis with <u>supervised learning</u> with real-world fault labels.
- Better understand how <u>KPI sampling granularity</u> will effect the anomaly prediction accuracy.