



3RD ALIBABA CLOUD AIOPS COMPETITION

第三届阿里云磐久智维算法大赛

“基于大规模日志的故障诊断”总决赛

基于树模型的AIOps故障根因分析与定位方法

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赛题分析

1、赛题理解

基于故障工单+系统日志数据，构建多分类模型，快速、高效的定位出故障类型。

2、评价指标

采用加权的F1-score，类别0和1赋予的权重更大。

初赛评价指标

- 综合四类，即「两种CPU故障」(0-1)、「内存故障」(2)和「其他故障」(3)，有

- 对应这四类的权重向量

$$w = \{\frac{3}{7}, \frac{2}{7}, \frac{1}{7}, \frac{1}{7}\}$$

- Macro F1-score

$$\text{Macro F1-score} = \sum_{i \in \{0,1,2,3\}} w_i \times \text{F1-score}_i$$

复赛评价指标

四个类别对应的权重向量为：

$$w = \{\frac{5}{11}, \frac{4}{11}, \frac{1}{11}, \frac{1}{11}\}$$

其余与初赛相同。

数据分析

1、数据样本

故障工单数据

sn	fault_time	label
SERVER_10001	2020-05-01 10:04:00	1
SERVER_10003	2020-03-28 09:48:00	2
SERVER_10008	2020-02-25 16:12:00	1
SERVER_10008	2020-03-11 18:04:00	2
SERVER_10009	2020-05-08 16:37:00	3
SERVER_10012	2020-07-13 03:32:00	3
SERVER_10017	2020-06-11 15:52:00	3
SERVER_10017	2020-06-11 15:52:00	3
SERVER_10018	2020-05-31 03:33:00	3
SERVER_10019	2020-01-29 22:38:00	3

故障日志

sn	time	msg	server_model
000d33b21436	2020-09-02 11:38:40	System Boot Initiated BIOS_Boot_Up Initiated by warm reset Asserted	SM40
000d33b21436	2020-09-02 15:46:23	System Boot Initiated BIOS_Boot_Up Initiated by power up Asserted	SM40
004d5a7954e7	2020-08-24 08:07:29	Memory CPU1D0_DIMM_Stat Uncorrectable ECC Asserted	SM35
004d5a7954e7	2020-08-24 08:07:30	Processor CPU0_Status Configuration Error Asserted	SM35
004d5a7954e7	2020-08-24 08:07:54	Processor CPU0_Status Configuration Error Asserted	SM35
004d5a7954e7	2020-08-24 08:07:54	Memory CPU1D0_DIMM_Stat Uncorrectable ECC Asserted	SM35
004d5a7954e7	2020-08-24 08:13:11	Memory CPU1D0_DIMM_Stat Correctable ECC Asserted	SM35
007bdf23b62f	2020-06-16 17:04:19	Memory #0xe2 Correctable ECC Asserted	SM93
007bdf23b62f	2020-06-16 17:10:54	Memory #0xe2 Correctable ECC Asserted	SM93
007bdf23b62f	2020-06-16 17:11:17	Memory #0xe2 Correctable ECC Asserted	SM93

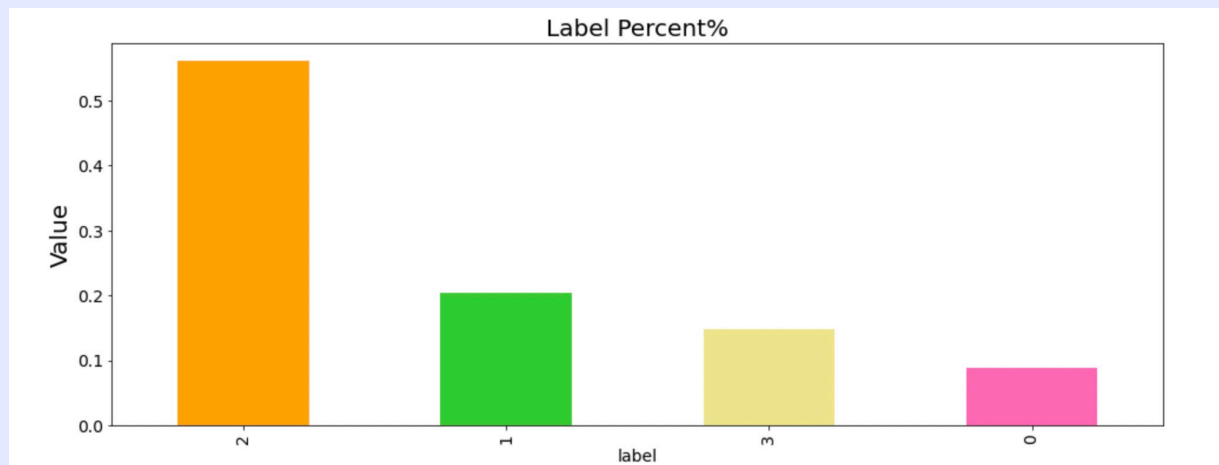
- 本赛题提供了故障工单与故障日志数据，具体数据如上图所示。通过初步分析日志结构，可以将其分解为右图数据。
- 初步认识：从服务器出现故障的业务场景出发，在故障发生的前后5/10/15/30分钟或更久，所产生的日志信息，都会与此故障有关。

msg_0	msg_1	msg_2
[' System Boot Initiated BIOS_Boot_Up']	['Initiated by warm reset']	['Asserted']
[' System Boot Initiated BIOS_Boot_Up']	['Initiated by power up']	['Asserted']
[' Memory CPU1D0_DIMM_Stat']	['Uncorrectable ECC']	['Asserted']
[' Processor CPU0_Status']	['Configuration Error']	['Asserted']
[' Processor CPU0_Status']	['Configuration Error']	['Asserted']
[' Memory CPU1D0_DIMM_Stat']	['Uncorrectable ECC']	['Asserted']
[' Memory CPU1D0_DIMM_Stat']	['Correctable ECC']	['Asserted']
[' Memory CPU1D0_DIMM_Stat']	['Uncorrectable ECC']	['Asserted']
[' Processor CPU0_Status']	['Configuration Error']	['Asserted']
[' Processor CPU0_Status']	['Configuration Error']	['Asserted']

数据分析

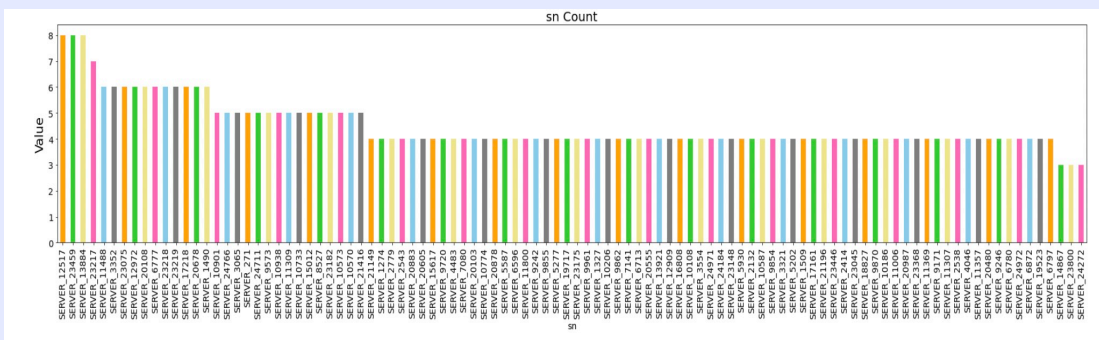
2、标签分布

- 4类标签：0类和1类表示CPU相关故障，2类表示内存相关故障，3类表示其他类型故障
- label_2占比最多，达到56%
- label_0占比最少，达到9%



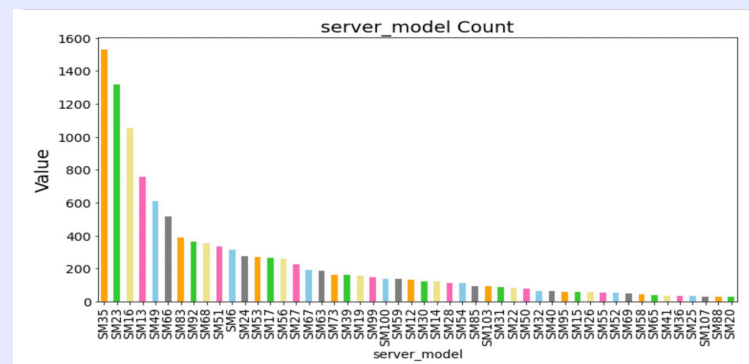
3、sn分布

- 唯一值达到13000+。



4、server_model分布

- 服务器型号server_model和服务器序列号sn是一对多的关系。



数据分析

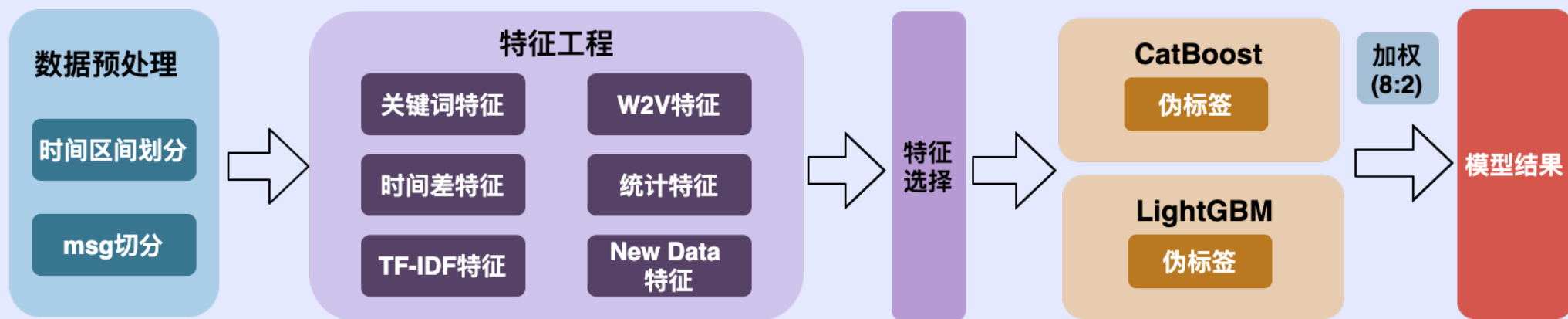
5、msg分析

- 将msg经过TF-IDF编码，输入到线性模型中，使用`eli5`得出每个类别下，msg单词的贡献程度，权重越高表示区分该类别的贡献越大；
- 0类和1类表示CPU相关故障，processor的权重都是最高的；
- 2类表示内存相关故障，权重较高的是memory、mem、ecc；
- 3类表示其他类型故障，权重较高的是hdd、fpga、bus。
- 推断出：
 - 0类和1类是cpu相关故障，且区分度不是很高
 - 3类可能是和硬件相关的故障

类别	权重高的单词	解释
label_0/label_1	processor	处理器
label_2	memory/mem	内存
	ecc	纠错码
label_3	hdd	硬盘驱动器
	fpga	可编程门阵列器件
	bus	计算机系统总线

y=0 top features		y=1 top features		y=2 top features		y=3 top features	
Weight?	Feature	Weight?	Feature	Weight?	Feature	Weight?	Feature
+3.787	processor	+4.773	processor	+6.943	memory	+3.634	hdd
+3.467	asserted	+4.261	mcerr	+6.734	uncorrectable	+3.156	failure
+3.035	ps0	+3.720	0xfa	+4.929	mem	+2.595	fpga
+3.025	ierr	+2.917	statususe	+4.872	ecc	+2.336	bus
+2.643	0x7d	+2.419	0xf5	+2.837	limit	+2.247	0x8c
+2.546	caterr	+2.403	0xbe	+2.827	reached	+2.229	0x10
+2.427	0x82	+2.367	0xf9	+2.544	0x8b	+2.150	0xe9
+2.380	0x3b	+2.352	pressed	+2.493	disabled	+2.071	fatal
+2.367	watchdog2	+2.227	deasserted	+2.370	hardware	+2.068	vr
+2.247	correctable	+2.158	0x7c	+2.336	che0	+2.037	log
+2.246	nvme SSD	+2.112	0x74	+2.267	limiting	+1.999	fault
+2.112	dimm101	+2.090	0xe4	+2.177	dimm	+1.996	restart
+2.072	0x13	+2.029	statusus	+2.092	device	+1.984	mngmnt
+2.044	mcerr	+1.976	cpu0	+2.087	recoverable	+1.964	sel
+1.999	thermal	+1.914	0xff	+2.052	dimm050	+1.960	dimm030
+1.910	inlet	+1.799	watchdog2	+2.031	0x84	+1.912	0x87
+1.896	0x0f	+1.736	0x3b	+1.999	0x90	+1.903	cpu1e1
+1.830	c3d1	+1.735	trip	+1.946	105	+1.830	dimm001
+1.822	c2d1	+1.735	dimm110	+1.940	undetermined	+1.811	dimm3a
+1.784	sta	+1.678	core	+1.922	dimm140	+1.800	detected
+1.732	cpu0	+1.673	ierr	+1.903	shutdown	+1.737	0xe2
+1.600	record	+1.673	running	+1.839	change	+1.706	cpu0d0
+1.598	000010003511	+1.625	correctable	+1.819	presence	+1.654	unit
+1.597	max	+1.624	dimm120	+1.789	watchdog	+1.638	controller
+1.597	tsb	+1.621	chg0	+1.743	0x75	+1.595	d0
+1.563	deasserted	+1.551	cpu2	+1.741	slot	+1.588	0x16
+1.549	c2	+1.435	dimm060	+1.714	0x96	+1.519	0x17
+1.546	temperature	+1.425	asserted	+1.610	0x98	+1.502	125
+1.545	0xfa	+1.391	lt	+1.596	bay	+1.472	powerlimiting
+1.467	ef	+1.387	prochot	+1.595	0x80	+1.464	0xef
+1.388	cpu3	+1.367	tota	+1.514	0x92	+1.439	bmc
+1.386	0xfe	+1.364	ipmi	+1.505	port2	+1.436	0x30
+1.380	dimm170	+1.339	present	+1.487	link	+1.389	12
+1.321	0x70	+1.293	0x71	+1.461	0x10	+1.366	specific
+1.317	d1	+1.277	ab	+1.439	0x8a	+1.340	100
+1.294	lan	+1.274	cpu0a1	+1.382	c5d0	+1.304	absent
+1.277	low	+1.271	critical	+1.369	dimm070	+1.298	interrupt

方案介绍



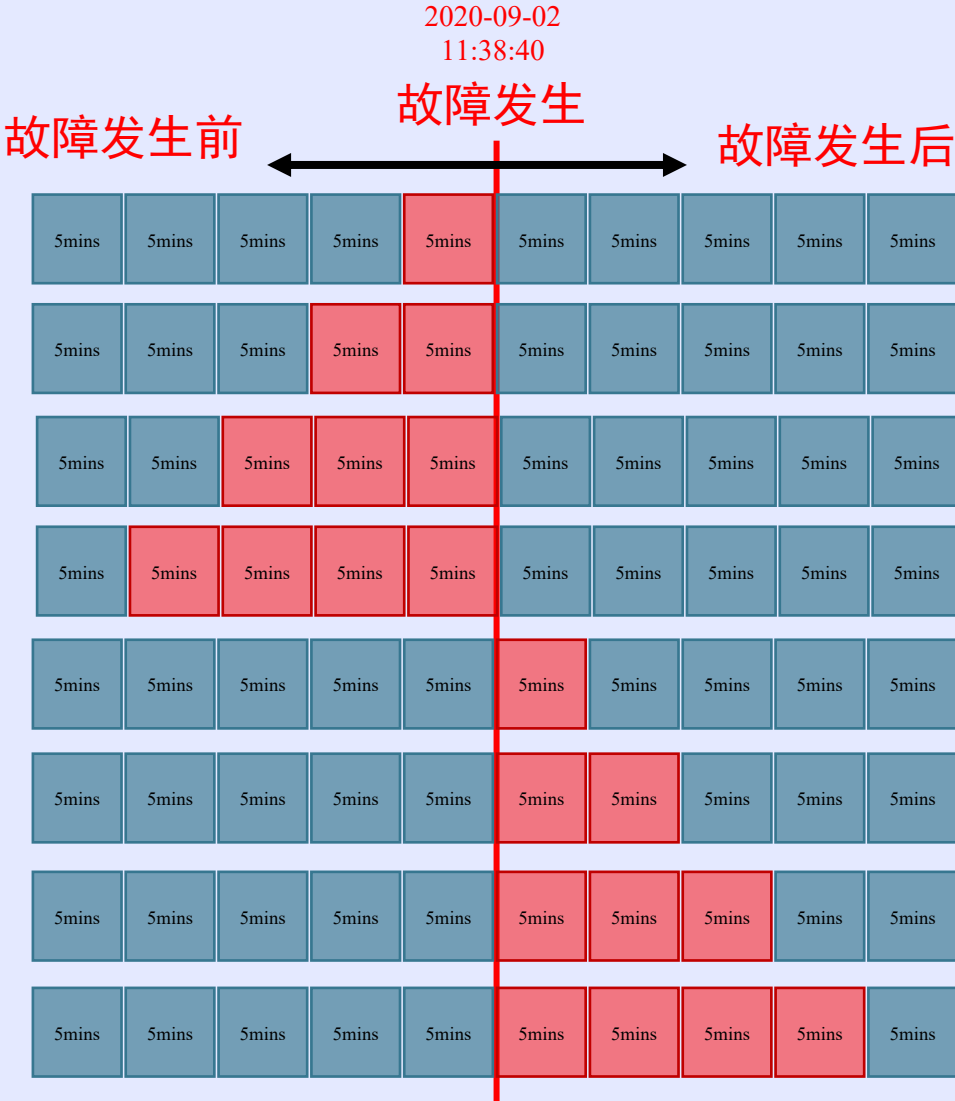
方案思想：基于智能运维场景，争取用更少的时间及资源达到最优效果，主要分为以下几个部分：

1. 数据预处理：按照距离故障发生时间的间隔，将日志分成不同的时间区间；msg根据特殊符号进行标准化。
2. 特征工程：主要构建关键词特征、时间差特征、TF-IDF词频统计特征、W2V特征、统计特征、New Data特征。
3. 特征选择：对抗验证进行特征选择，保证训练和测试集的一致性，提高模型在测试集的泛化能力。
4. 模型训练：CatBoost与LightGBM使用伪标签技术进行模型训练。
5. 模型融合：CatBoost与LightGBM的预测结果以8:2进行加权融合得到最终的模型预测结果。

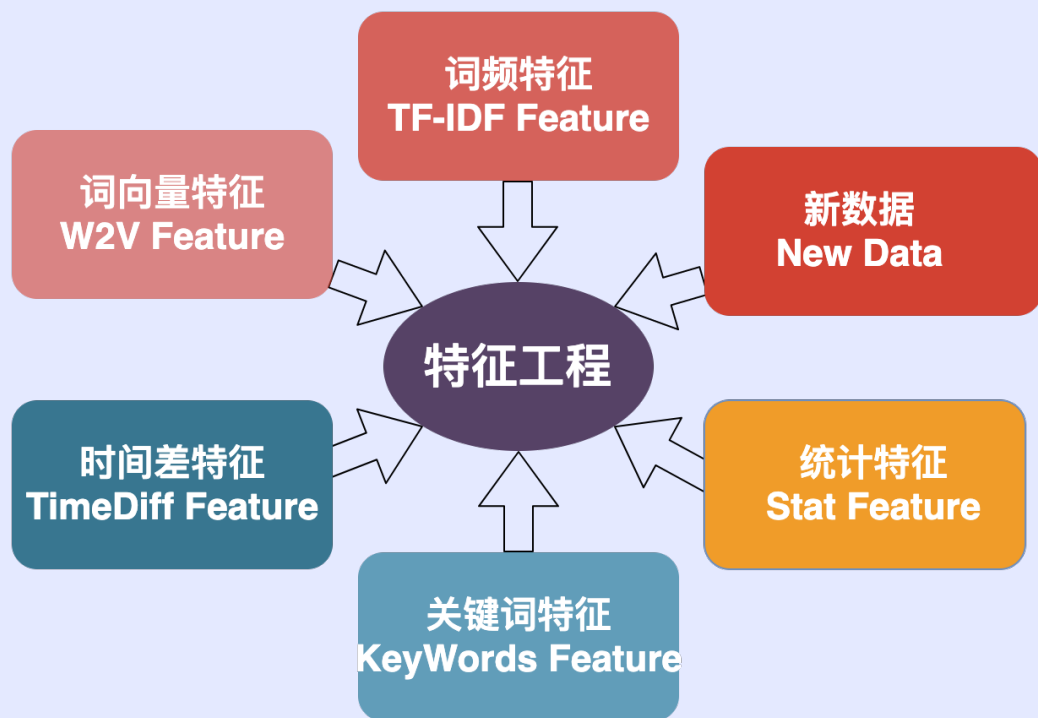
方案介绍—数据预处理

针对每一条故障工单，构造日志数据，用于后续的特征工程：

- 故障发生时间前5/10/15/30/60/120等分钟的日志数据
- 故障发生时间后5/10/15/30/60/120等分钟的日志数据
- 构造的每一份日志数据，都可以用于聚合构造统计特征



方案介绍—特征工程

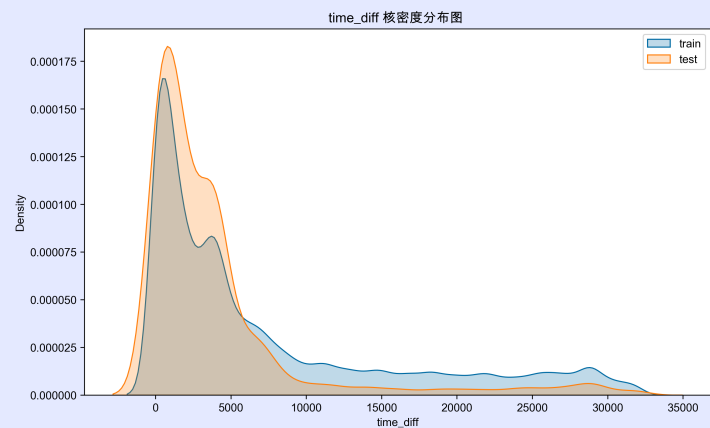


本方案从以下几个层面构建特征：

1. 时间差特征：反映故障日志与正常日志发生的间隔。
2. TF-IDF词频特征：反映每个词对每个类别的重要性。
3. W2V特征：反映msg的语义信息。
4. 统计特征：根据类别特征分组构造统计特征，使类别特征隐藏的信息充分暴露出来。
5. 关键词特征：反映关键词对各个类别的影响。
6. 新数据特征：新数据建模，预测结果作为新的特征。

方案介绍—特征工程

1、时间差特征



- 获取日志时间和故障发生时间的时间差，并且结合sn, server_model, 进行分组特征衍生。
- 时间差的统计特征：[max, min, median, std, var, skw, sum, mode]
- 时间差的分位数特征：[0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9]
- 时间差差分: [max, min, median, std, var, skw, sum]

2、关键词特征

y=0 top features		y=1 top features		y=2 top features		y=3 top features	
Weight?	Feature	Weight?	Feature	Weight?	Feature	Weight?	Feature
+3.787	processor	+4.773	processor	+6.943	memory	+3.634	hdd
+3.167	asserted	+4.261	mcerr	+6.734	uncorrectable	+3.156	failure
+3.035	ps0	+3.720	0xfa	+4.929	mem	+2.595	fpga
+3.025	ierr	+2.917	statususe	+4.872	ecc	+2.336	bus
+2.643	0x7d	+2.419	0xf5	+2.837	limit	+2.247	0x8c
+2.546	caterr	+2.403	0xbe	+2.827	reached	+2.229	0x10
+2.427	0x82	+2.367	0xf9	+2.544	0x8b	+2.150	0xe9
+2.380	0x3b	+2.352	pressed	+2.493	disabled	+2.071	fatal
+2.367	watchdog2	+2.227	deasserted	+2.370	hardware	+2.068	vr
+2.247	correctable	+2.158	0x7c	+2.336	che0	+2.037	log
+2.246	nvmesd	+2.112	0x74	+2.267	limiting	+1.999	fault
+2.112	dimmm101	+2.090	0xe4	+2.177	dimmm	+1.996	restart
+2.072	0x13	+2.029	status	+2.092	device	+1.984	mngmnt
+2.044	mcerr	+1.976	cpu0	+2.087	recoverable	+1.964	sel
+1.999	thermal	+1.914	0xff	+2.052	dimmm050	+1.960	dimmm030
+1.910	inlet	+1.799	watchdog2	+2.031	0x84	+1.912	0x87
+1.896	0xf0	+1.736	0x3b	+1.999	0x90	+1.903	cpu1e1
+1.830	c3d1	+1.735	trip	+1.946	105	+1.830	dimmm001
+1.822	c2d1	+1.735	dimmm110	+1.940	undetermined	+1.811	dimmm3a
+1.784	sta	+1.678	core	+1.922	dimmm140	+1.800	detected
+1.732	cpu0	+1.673	ierr	+1.903	shutdown	+1.737	0xe2
+1.600	record	+1.673	running	+1.839	change	+1.706	cpu0d0
+1.598	000010003511	+1.625	correctable	+1.819	presence	+1.654	unit

	fea	fea_cnt_0	fea_cnt_1	fea_cnt_2	fea_cnt_3	fea_cnt_ratio_std	fea_max
Reading 87 > Threshold 85 degrees C	25	1	1	1		0.428571	0
OEM record c2	367	26	13	8		0.424711	0
Processor CPU_Core_Error	369	37	15	11		0.403646	0
Reading 71 > Threshold 85 degrees C	10	1	1	1		0.346154	0
Reading 86 > Threshold 85 degrees C	30	3	3	5		0.321960	0
OEM CPU0 CATERR	133	348	1	3		0.336693	1
OEM CPU0 MCERR	133	349	1	3		0.336953	1
Reading 0 < Threshold 2 degrees C	112	270	2	1		0.329890	1
Microcontroller #0xff	15	117	1	7		0.392619	1
S5/G2: soft-off	2	89	22	6		0.339782	1
Memory	1	14	9401	15		0.497880	2
Correctable ECC logging limit reached	9	152	7914	20		0.485160	2
Memory MEM_CHE0_Status	2	4	302	1		0.484914	2
Memory #0x87	266	147	17141	661		0.460850	2
Memory Memory_Status	169	74	4007	14		0.460062	2
Power Supply FPGA_PG	1	3	1	58		0.447340	3
Drive Fault	36	17	142	6426		0.476969	3
NMI/Diag Interrupt	4	20	2	510		0.467903	3
Failure detected	34	110	61	3034		0.457909	3
Drive Slot / Bay HDD_L_2_Status	4	1	1	62		0.441666	3

- 将msg经过TF-IDF编码，输入到线性模型中，计算每个类别下关键词的权重，取每个类别的TOP20。
- 根据'|'对msg进行分词，统计每个类别的词频占比，取每个类别的TOP20。
- 方法1与方法2取并集，得到最终的关键词。
- 每个关键词在msg中出现与否作为特征。

方法1：基于TF-IDF模型

方法2: 基于词袋模型(统计词频数)

方案介绍—特征工程

3、统计特征

- 根据sn分组，server_mode统计特征:[count,nunique,freq,rank]
- 根据sn分组，日志统计特征：msg, msg_0, msg_1, msg_2:[count,nunique,freq,rank]

4、W2V特征

- 根据sn分组，按照时间对msg进行排序，对于每一个sn，将排序好的msg作为一个序列，提取embedding特征。

sn	msg_list
SERVER_10001	['Processor CPU1_Status', 'IERR', 'Asserted', 'Processor CPU0_Status', 'IERR', 'Asserted', 'Management Subsys Health System_Health', 'Sensor acce...
SERVER_10003	['Memory CPU1D0_DIMM_Stat', 'Correctable ECC', 'Asserted', 'Memory CPU1D0_DIMM_Stat', 'Correctable ECC', 'Asserted', 'Memory CPU1D0_DIM...
SERVER_10008	['Memory DIMM050_Stat', 'Uncorrectable ECC', 'Asserted', 'Processor CPU0_Status', 'Configuration Error', 'Asserted', 'Processor CPU0_Status', 'Co...
SERVER_10009	['Drive Slot HDD_L_14_Status', 'Drive Fault', 'Asserted', 'Drive Slot / Bay HDD_L_14_Status', 'Drive Fault', 'Asserted', 'Drive Slot HDD_L_14_Status', '...

5、TF-IDF特征

- 根据fault_id分组，对于每一个fault_id，将msg拼接作为一个序列，提取TF-IDF特征。

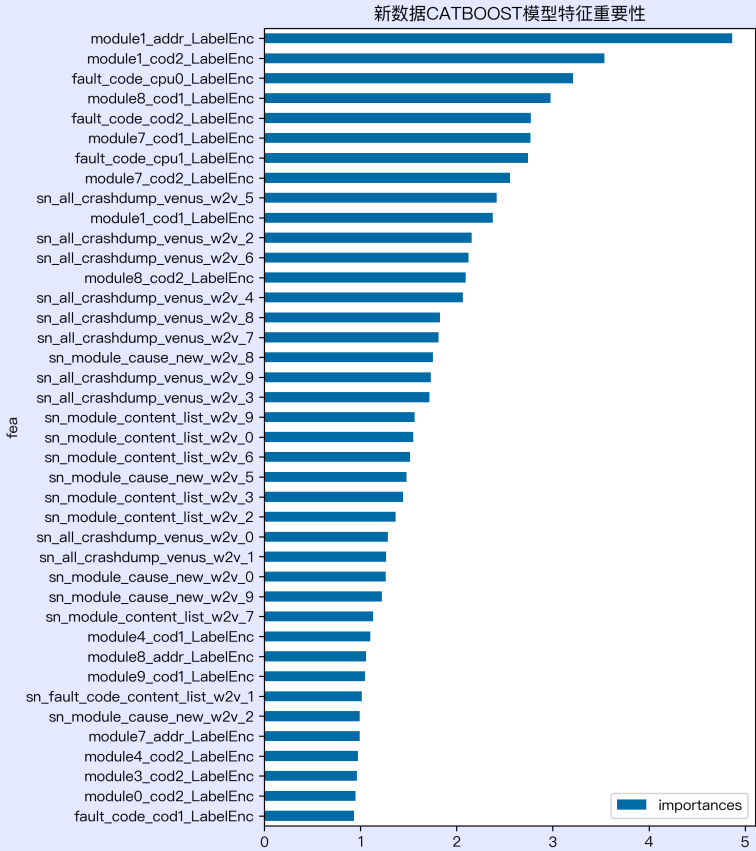
方案介绍—特征工程

6、venus、crashdump日志新数据特征构造

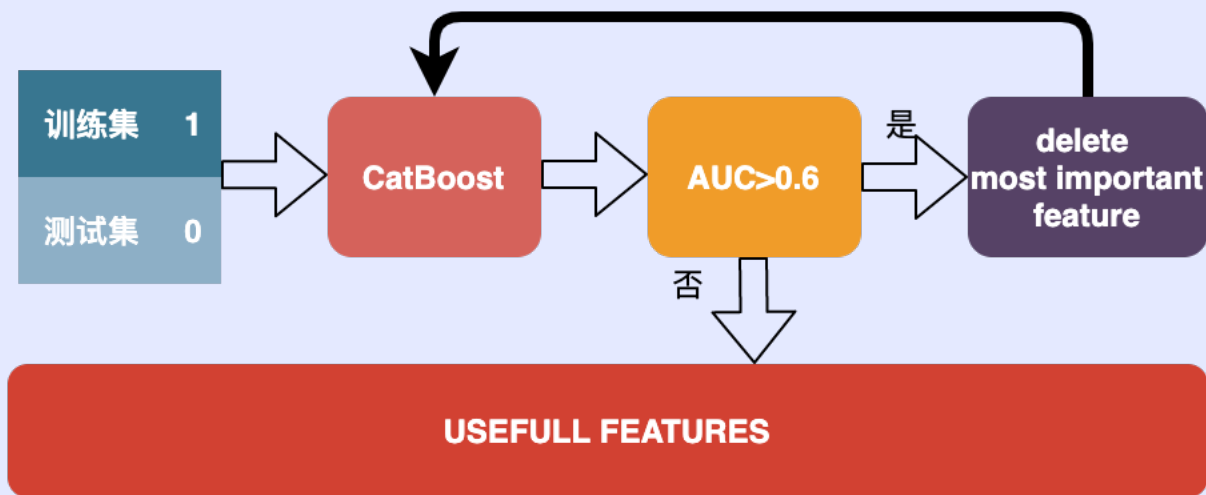
	fault_code_list	fault_code_cod1	fault_code_cod2	fault_code_cpu0	fault_code_cpu1
0	[cpu0, cha14, cod2, 0xc]	[' ']	['0xc']	['cha14']	[' ']
1	[cpu0, cha21, cod2, 0xc]	[' ']	['0xc']	['cha21']	[' ']
2	[cpu1, core0, cod1, 0x00800400]	['0x00800400']	[' ']	[' ']	['core0']
3	[cpu1, cha21, cod2, 0xc]	[' ']	['0xc']	[' ']	['cha21']
4	[cpu0, cha8, cod2, 0xc]	[' ']	['0xc']	['cha8']	[' ']
...	...	...	...	...	...
101	[cpu1, core25, cod1, 0x00000114]	['0x00000114']	[' ']	[' ']	['core25']
102	[cpu0, m2m0, cod2, 0x1]	[' ']	['0x1']	['m2m0']	[' ']
103	[cpu0, cha8, cod2, 0xc]	[' ']	['0xc']	['cha8']	[' ']
104	[cpu1, m2m0, cod2, 0x1]	[' ']	['0x1']	[' ']	['m2m0']
105	[cpu0, m2m0, cod2, 0x4]	[' ']	['0x4']	['m2m0']	[' ']

	module_cause_list	module3_cod1	module3_cod2	module3_addr	module4_cod1	module4_cod2	module4_addr
0	[module10, cod1:0x110a, cod2:0xc, addr:0x104bf...	['0x400']	['0x80']	['0xffffffff810779ab']	['0x400']	['0x80']	['0x7fbb95ddc4a']
1	[module9, cod1:0x110a, cod2:0xc, addr:0xee501000]	[' ']	[' ']	[' ']	[' ']	[' ']	[' ']
2	[module3, cod1:0x400, cod2:0x80, addr:0x7f9455...	['0x400']	['0x80']	['0x7f945563bfd']	['0x400']	['0x80']	['0x7f945563bfd']
3	[module9, cod1:0x110a, cod2:0xc, addr:0xee501000]	[' ']	[' ']	[' ']	[' ']	[' ']	[' ']
4	[module11, cod1:0x110a, cod2:0xc, addr:0xc5d01...	[' ']	[' ']	[' ']	[' ']	[' ']	[' ']
...	...	...	...	...	...	...	...
101	[module1, cod1:0x114, cod2:0x0, addr:0x5e55c53...	[' ']	[' ']	[' ']	[' ']	[' ']	[' ']
102	[module7, cod1:0x92, cod2:0x101, addr:0xbd6f45...	[' ']	[' ']	[' ']	[' ']	[' ']	[' ']
103	[module11, cod1:0x110a, cod2:0xc, addr:0x40, m...	['0x400']	['0x80']	['0x564447b2f197']	['0x400']	['0x80']	['0x564447b2f197']
104	[module1, cod1:0x134, cod2:0x10, addr:0xb72c2a...	[' ']	[' ']	[' ']	[' ']	[' ']	[' ']
105	[module1, cod1:0x134, cod2:0x10, addr:0x6ff4a000]	[' ']	[' ']	[' ']	[' ']	[' ']	[' ']

- 对新数据的数据格式进行标准化，关键词提取，生成类别特征。
- 通过新数据提取的特征构造模型，预测结果作为特征，与旧数据特征一起训练，新数据模型特征重要性如下：



方案介绍—特征选择

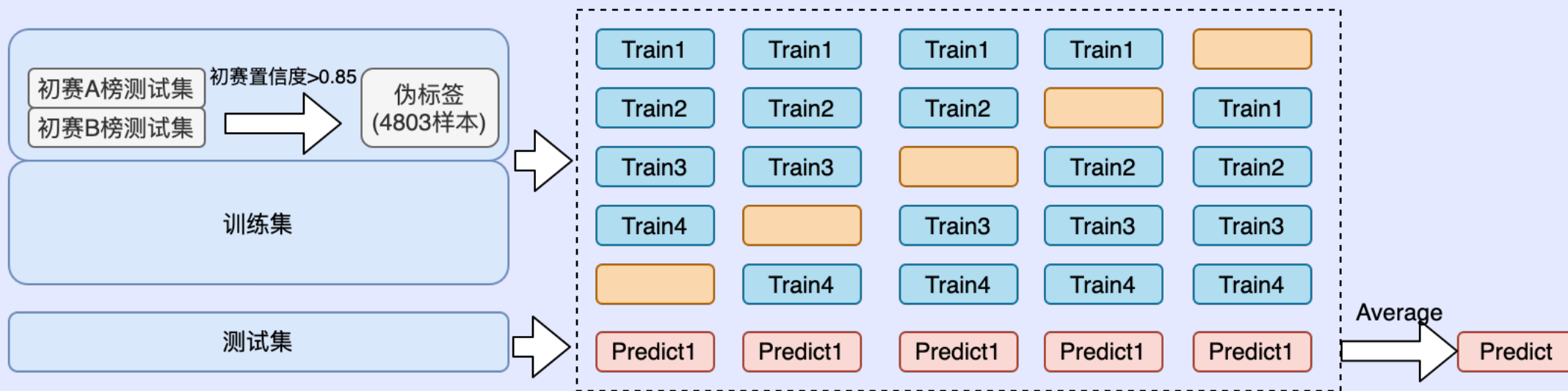


对抗验证特征选择

1. 准备好已完成特征构造的训练集和测试集。
2. 删除label，重新打标，训练集为1，测试集为0。
3. 数据集合并，训练 CatBoost 模型，计算AUC。
4. 设置一定的阈值(默认阈值为0.6，阈值必须大于0.5)。
5. 若AUC大于阈值，删除特征重要性最高的特征，重新执行第3步。
6. 所有第5步中被删除的特征，就是最终获得的训练集和测试集分布不一致的特征，不推荐在后续过程中使用。

方案介绍—模型训练

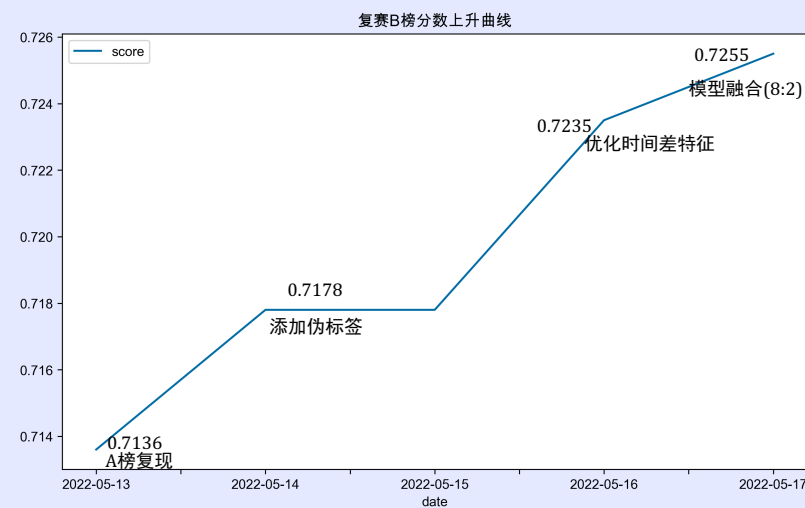
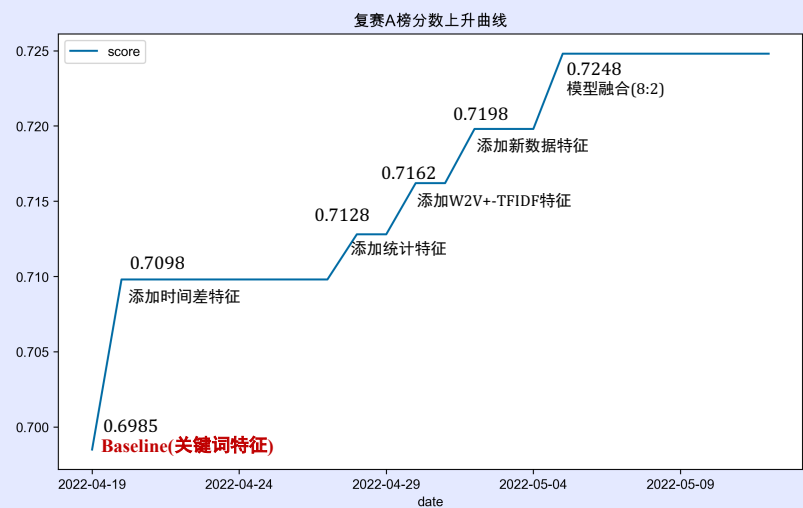
对于CatBoost与LightGBM均进行五折交叉构造出5个模型，将预测出来的结果进行平均作为单模型最终结果，以保证模型的稳定性。最终 CatBoost 与 LightGBM 的预测结果以8:2进行加权。



伪标签技术：

- 将A、B榜测试集的数据，选取模型预测结果置信度>0.85的样本作为可信样本，加入到训练集中，增大样本量。

方案介绍—模型效果



本方案代码运行环境基于8核32G服务器。主要使用两套特征模型，CatBoost 模型主要依赖统计与关键词特征，复赛B榜单模得分 0.7235，预测总耗时**仅需00:01:45（约0.04秒/条）**；LightGBM 模型主要依赖TF-IDF特征与W2V特征，复赛B榜单模得分 0.7167，预测耗时约**仅需00:02:07（约0.04秒/条）**。两者融合模型得分0.7255。

	CatBoost 模型		LightGBM 模型	
	训练耗时	预测耗时	训练耗时	预测耗时
特征工程	0:18:19	0:01:44	0:22:38	0:02:05
模型层	0:06:31	0:00:01	0:07:20	0:00:02
总耗时	52:39:01	0:01:45	66:25:06	0:02:07

总结展望

1. 模型方案要考虑到落地情况。如智能运维场景下，计算资源一般不会太多，或没有GPU资源，部分场景要求高及时性，越快找到问题并解决，就能越快的恢复对应的业务线。
2. 问题分析一定要考虑业务层面。想到可能有用的稍微有一点业务含义的特征就添加，哪怕不太确定，或者觉得和已有特征关联较大。
3. 使用对抗验证进行特征选择，保证训练集测试集的一致性，是提高模型准确性的关键。
4. 对msg信息的充分挖掘，也使得模型在AB榜测试相对稳定。

The background is a dark blue, futuristic scene. On the left and right sides, there are wireframe models of human heads in profile, facing each other. The wireframes are composed of glowing purple and blue lines. In the center, the word "THANKS!" is written in a large, bold, white sans-serif font. The letters have a slight 3D effect with red and blue outlines. The background also features various geometric shapes, including a large triangle in the center, and some faint, glowing lines and shapes that suggest a high-tech or digital environment.

THANKS!