

Data Science in Search for Best Predictions of **Ski Tour Difficulties**



FANS nettverksmøte | Data Science/Analytics | 13.3.2024 | Oslo

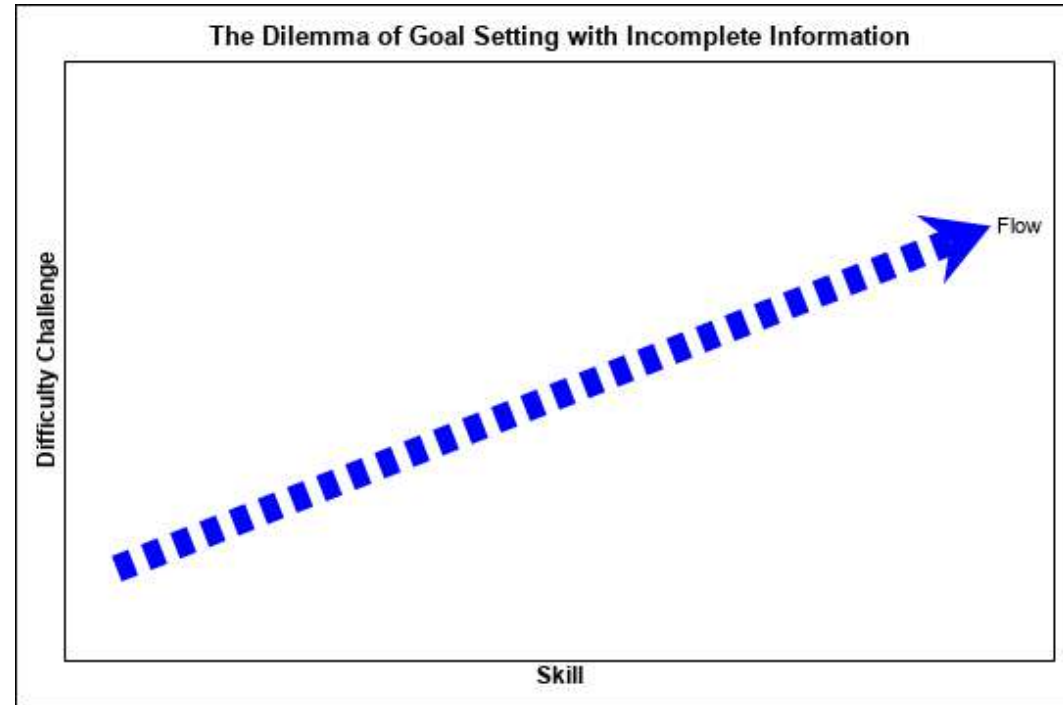
*Günter Schmudlach, Skitouren guru.com
Ulrich Reincke, SAS Institute*

Difficulty of a ski tour

Why is it important?

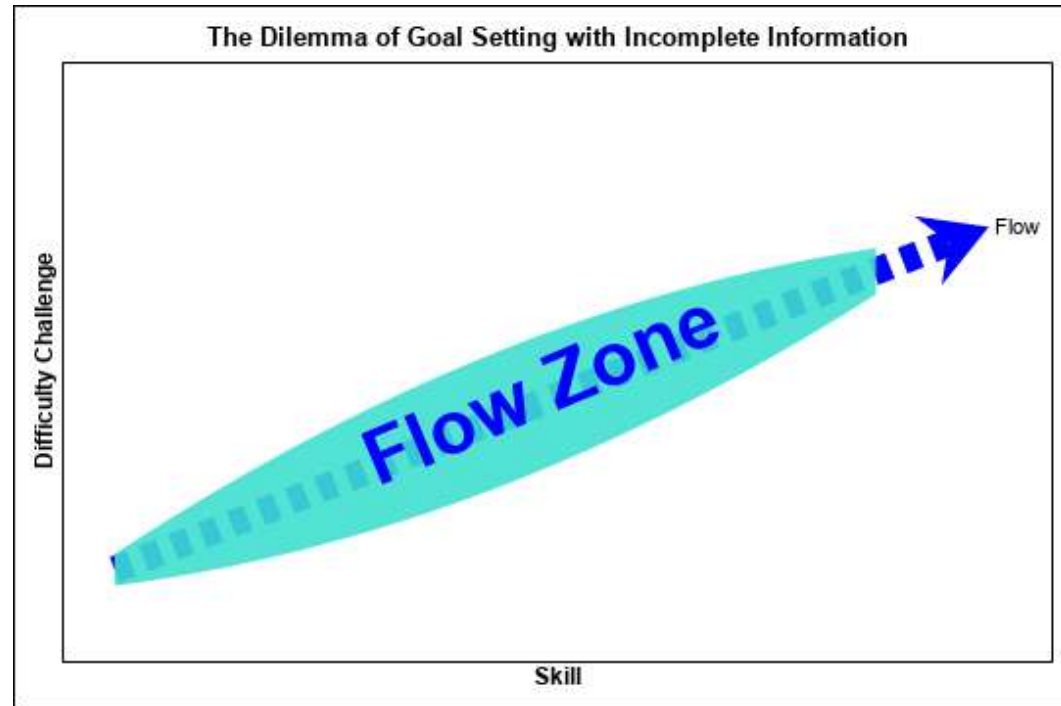
Difficulty of a ski tour

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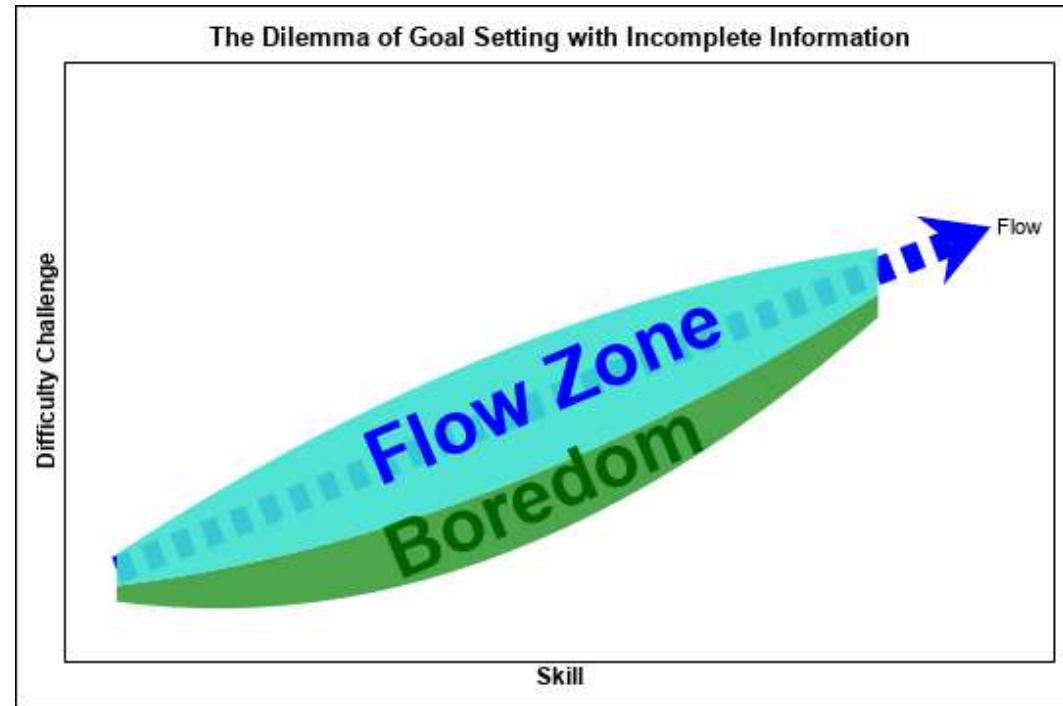
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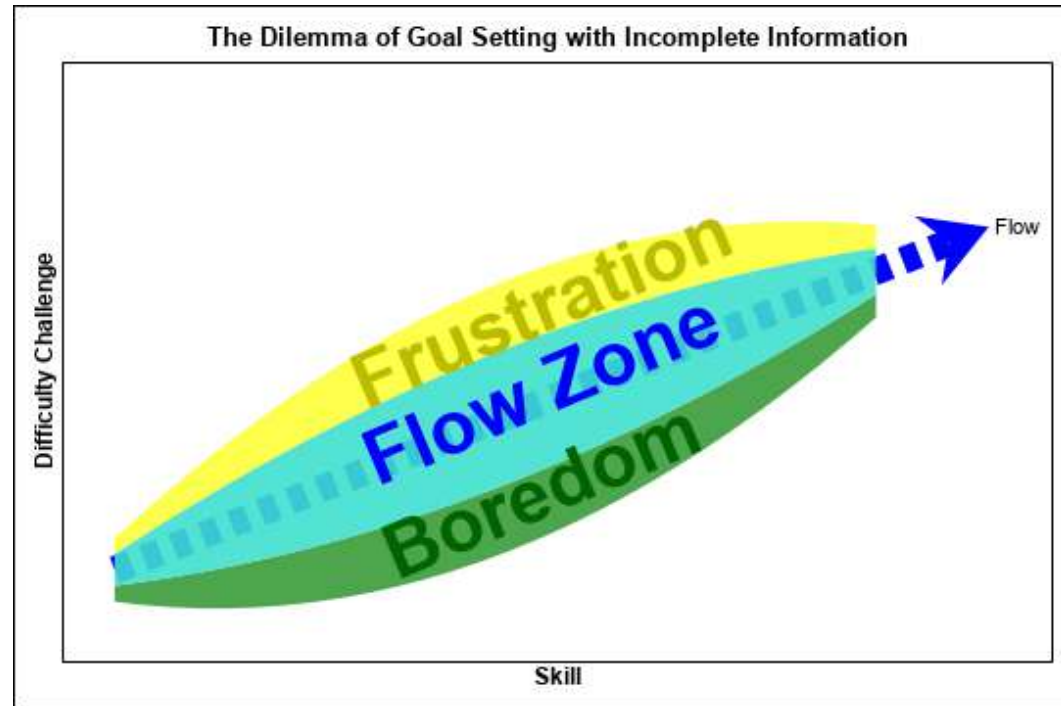
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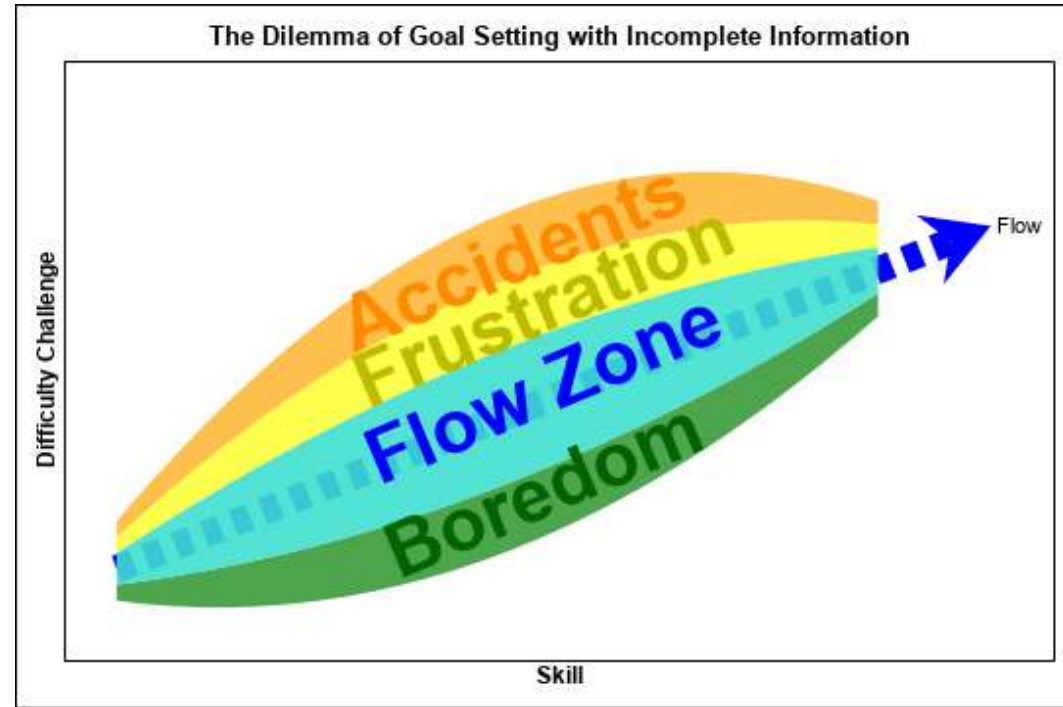
Difficulty of a ski tour

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Difficulty of a ski tour

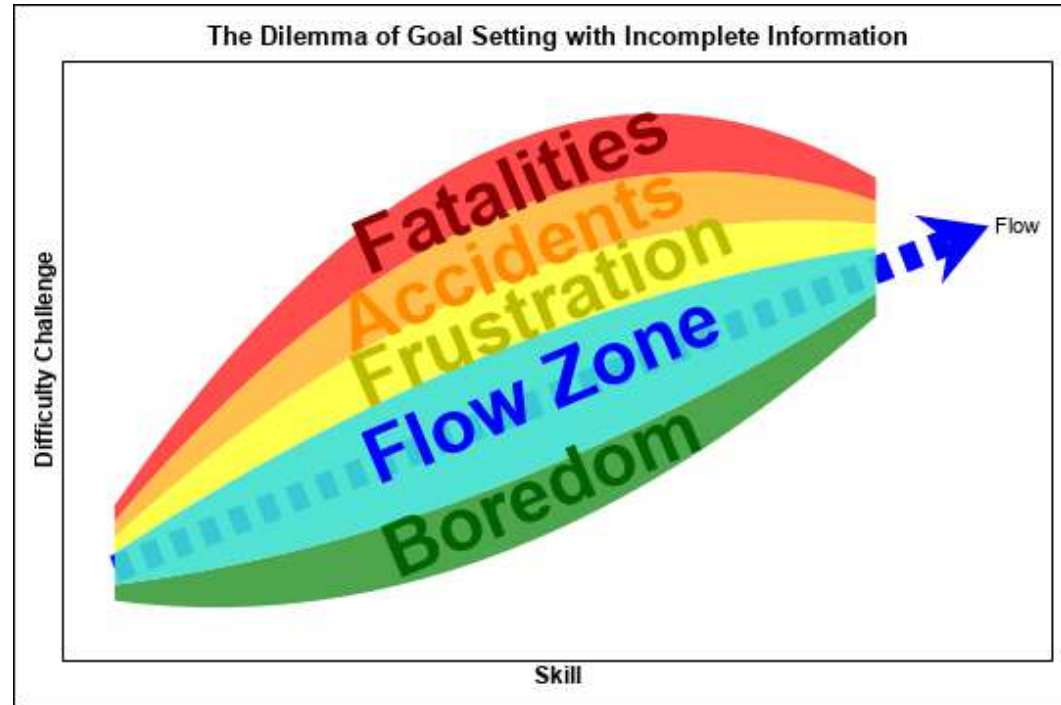
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Difficulty of a ski tour

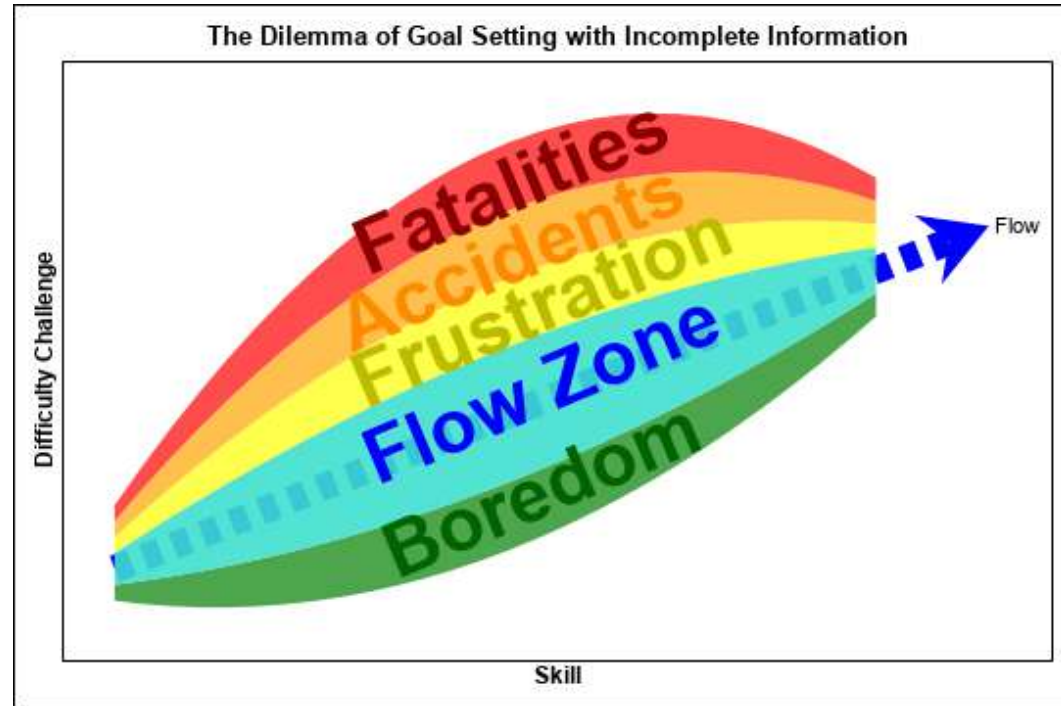
Why is it important?

Yearly official alpine accident statistics:
~70 fatalities of ~400 severe avalanche accidents
~25 fatalities of ~1000 severe ski tour accidents (non-avalanche)



Knowledge of a tour's difficulties is important for Better tour preparation, reduction of accidents and fatalities

Yearly official alpine accident statistics:
~70 fatalities of ~400 severe avalanche accidents
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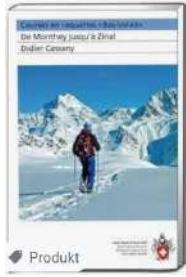
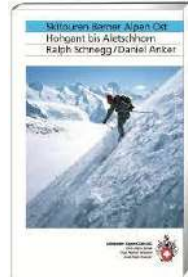
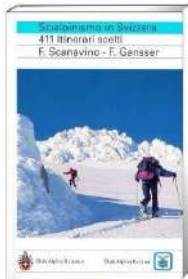


$$DIFFICULTY = f(\text{SlopeAngle, SpeedMax, Curvature, Forestation, ...})$$

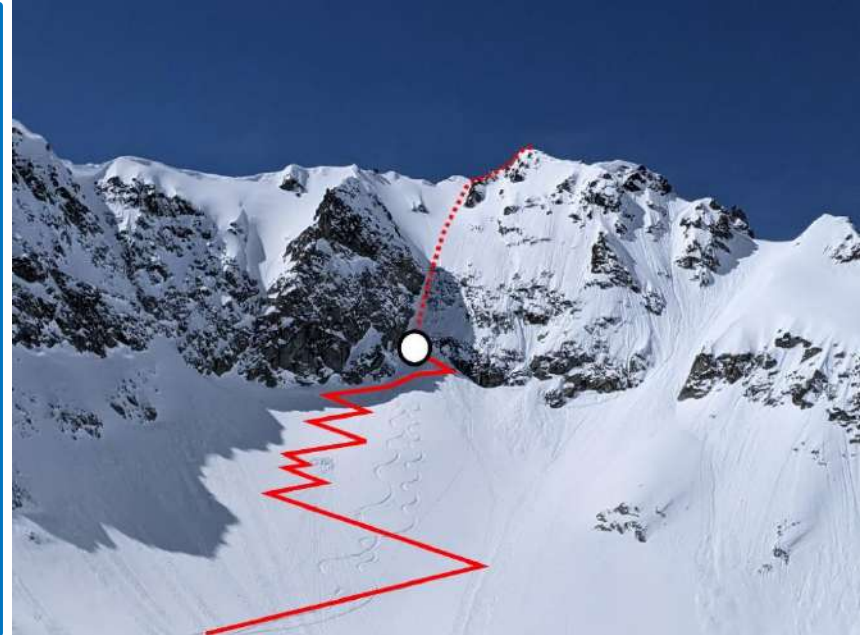
Dependent Variable: Difficulty

N=1307 Swiss Ski Tours,

Published in Swiss ski touring literature:



DIFFICULTY	DIFFICULTY LABEL
1	Easy
2	Easy (+)
3	Less Difficult (-)
4	Less Difficult
5	Less Difficult (+)
6	Quite Difficult (-)
7	Quite Difficult
8	Quite Difficult (+)
9	Difficult (-)
10	Difficult
11	Difficult (+)
12	Very Difficult (-)
13	Very Difficult
14	Very Difficult (+)
15	Extremely Difficult (-)
16	Extremely Difficult
17	Extremely Difficult (+)
18	Extremely Difficult



According to the SAC methodology, the difficulty level should only reflect the ski section of a tour up to the ski depot

Main criteria for the SAC difficulty scale

steepness, exposure to fall down, space conditions



steepness: slope angle



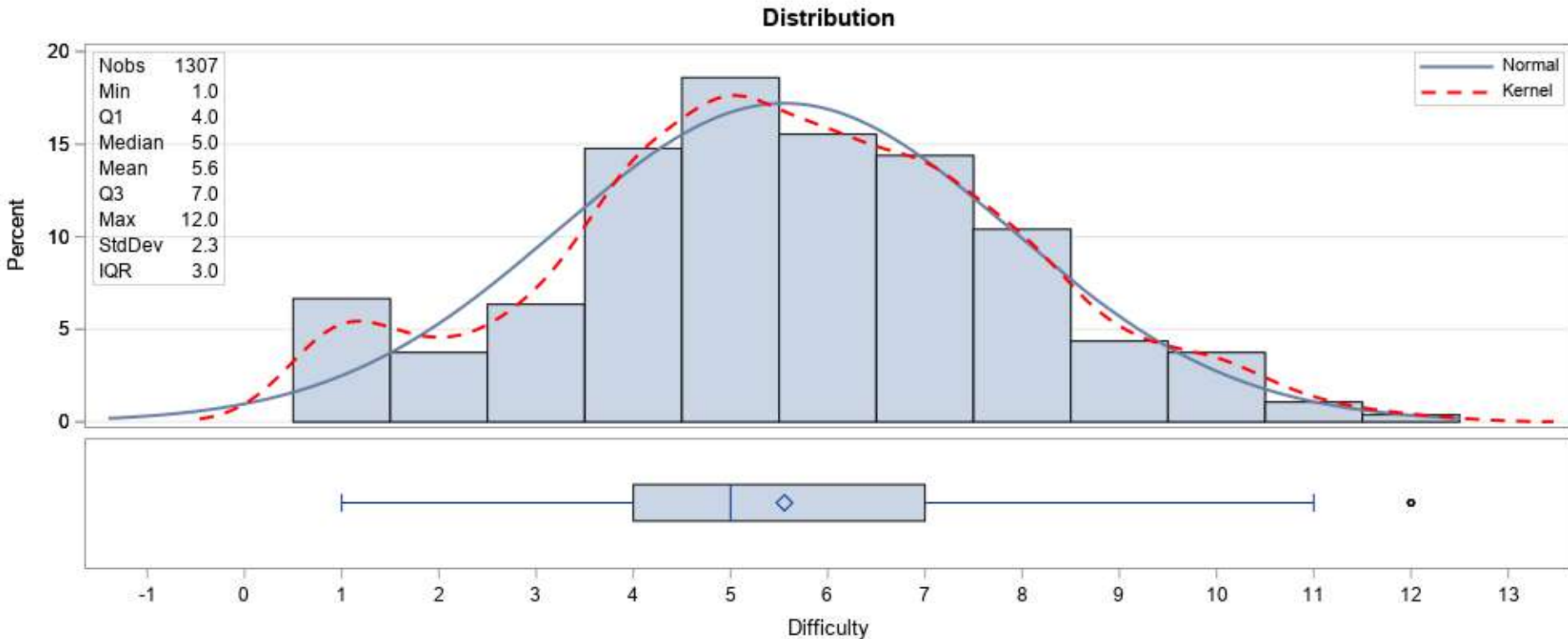
exposure to fall: speed max



space conditions: corridor width

target variable / dependent variable

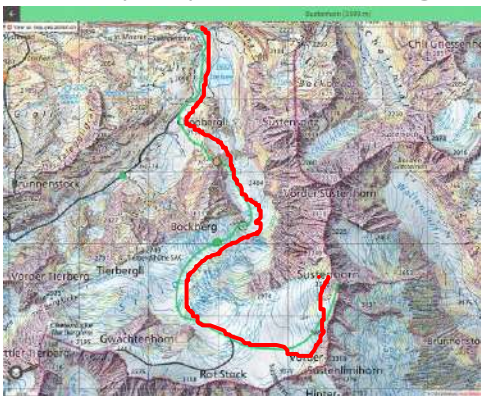
ski tour difficulty from SAC literature



Data preparation: from properties to prediction features

N=1307 Swiss tours, ~9.3 mill. track meters

Local properties along each **Track**:

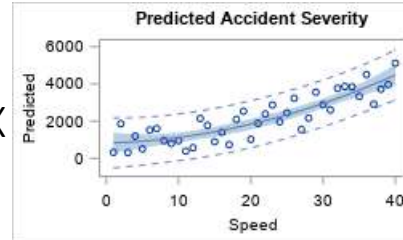
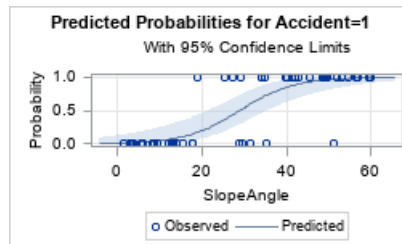
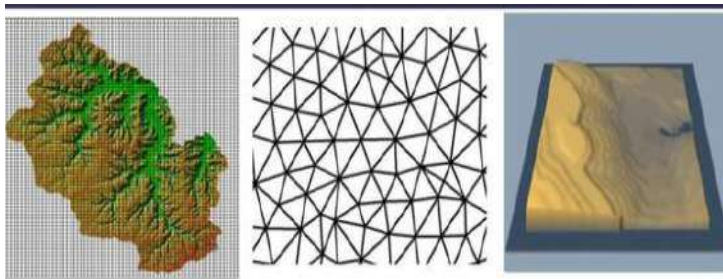


Properties:

- SlopeAngle (x,y) „steepness“
- SpeedMax (x,y) „exposure to fall“
- Width (x,y) „space conditions“
- Forestation (x,y)
- Curvature (x,y)
- Fold (x,y)

$$\text{-Risk}(x,y) := \text{SlopeAngle}(x,y) * \text{SpeedMax}(x,y)$$

Digital Landscape Model 10m*10m



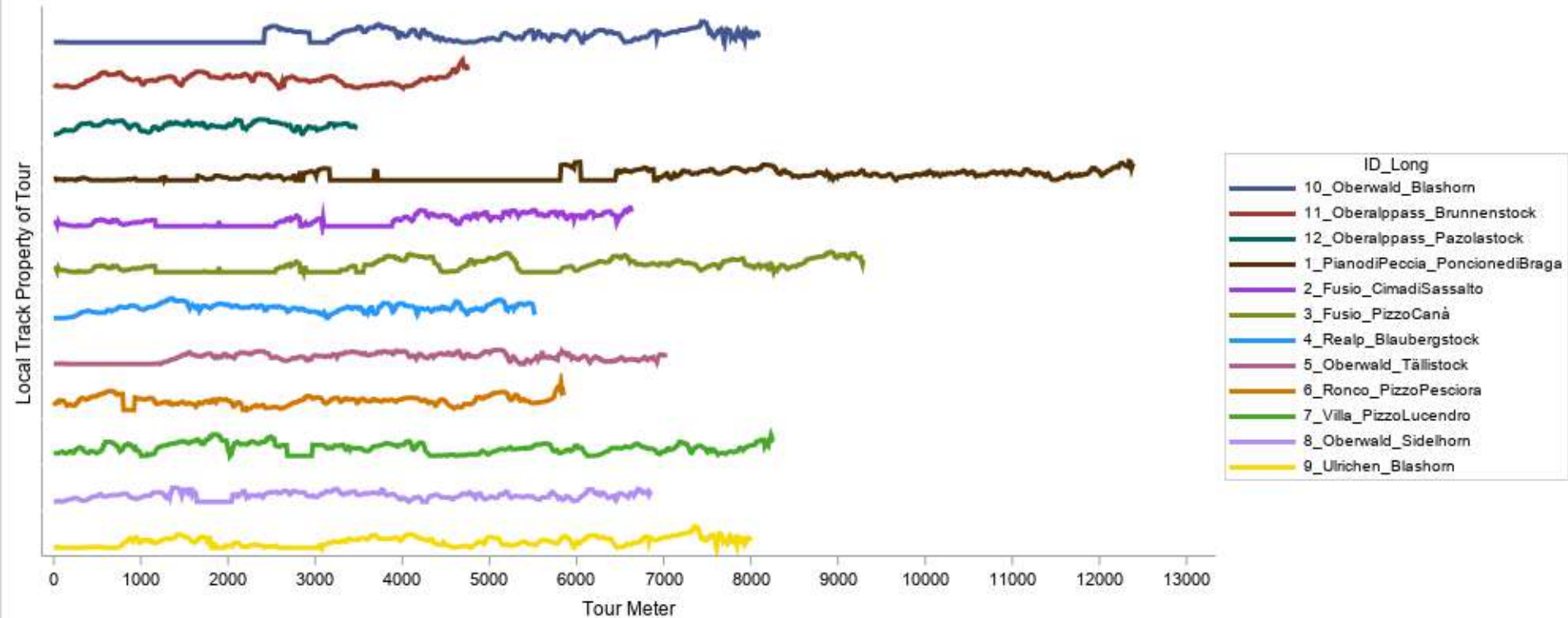
Data preparation

from local track properties to unique tour features

Data preparation

from local track properties to unique tour features

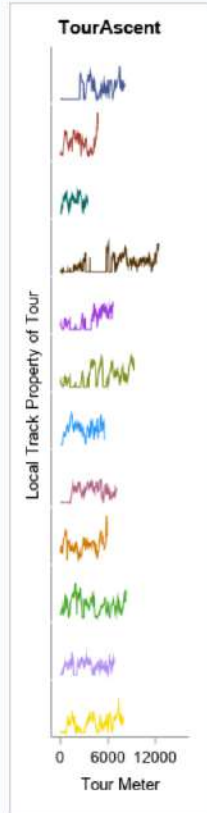
Illustrative example of a local property along tours in ascent



Local track properties of tours processed: Risk, Slope Angle, SpeedMax, Acceleration, Forestation, Curvature, Width,...

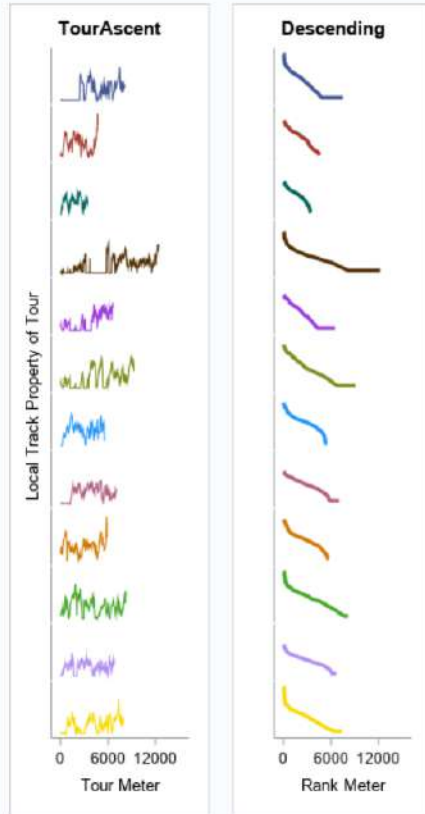
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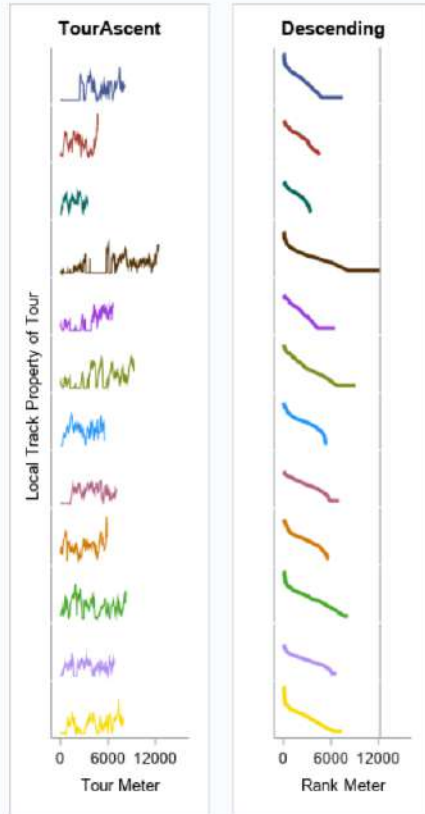
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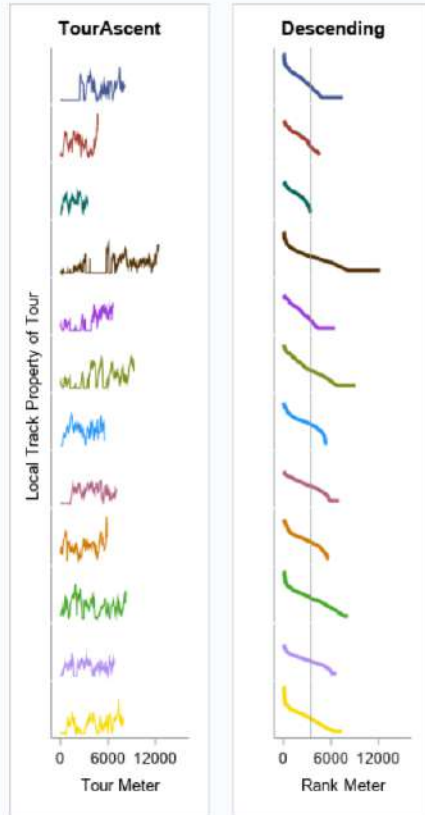
Data preparation

from local track properties to unique tour features



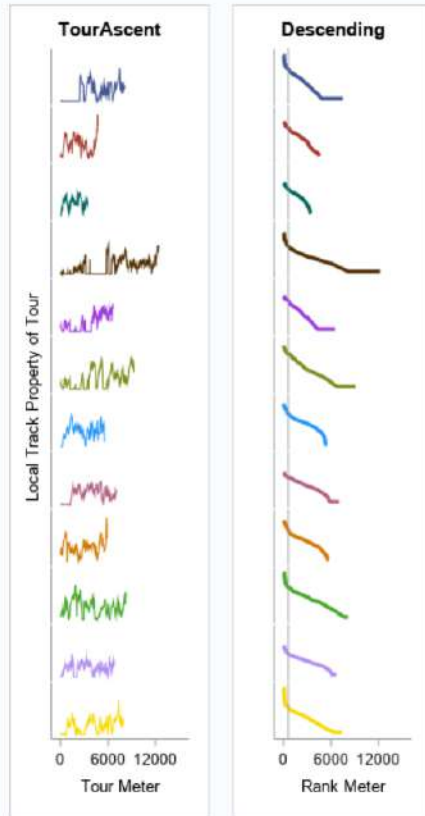
Data preparation

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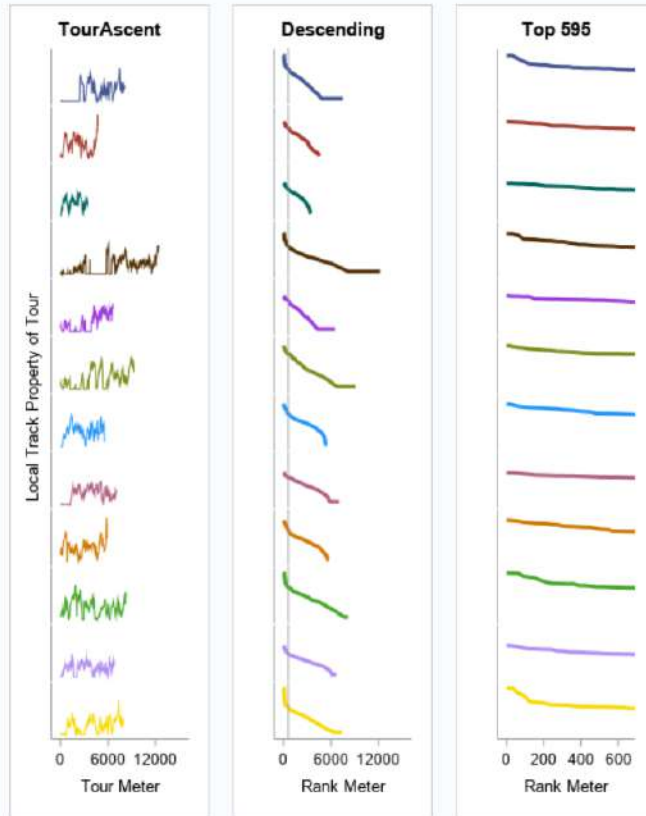
Data preparation

from local track properties to unique tour features



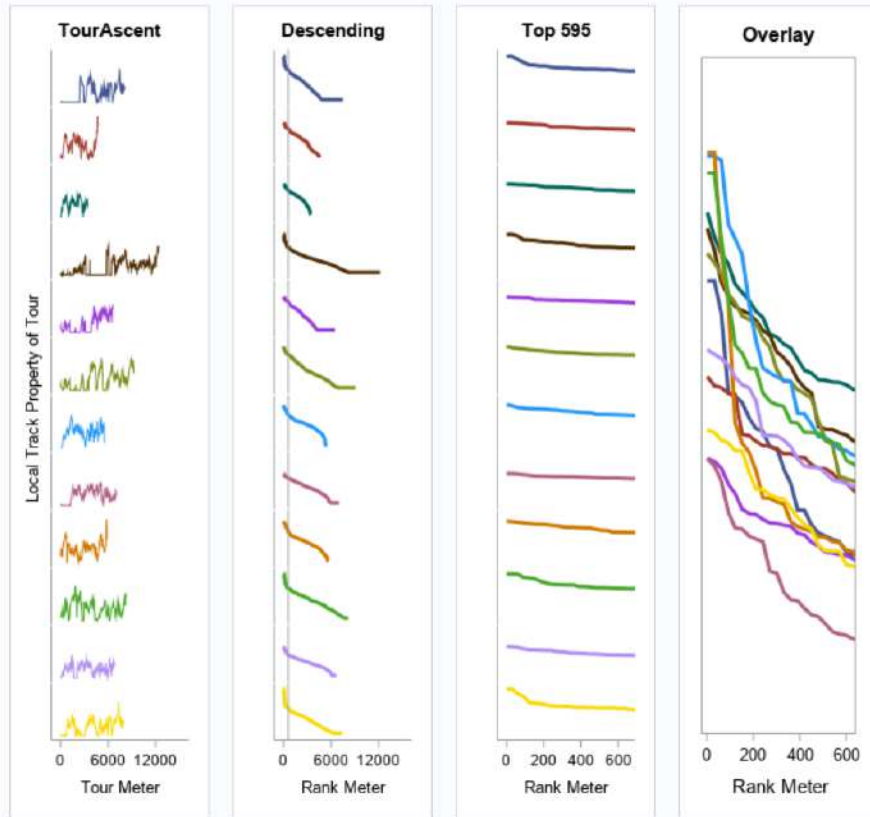
Data preparation

from local track properties to unique tour features



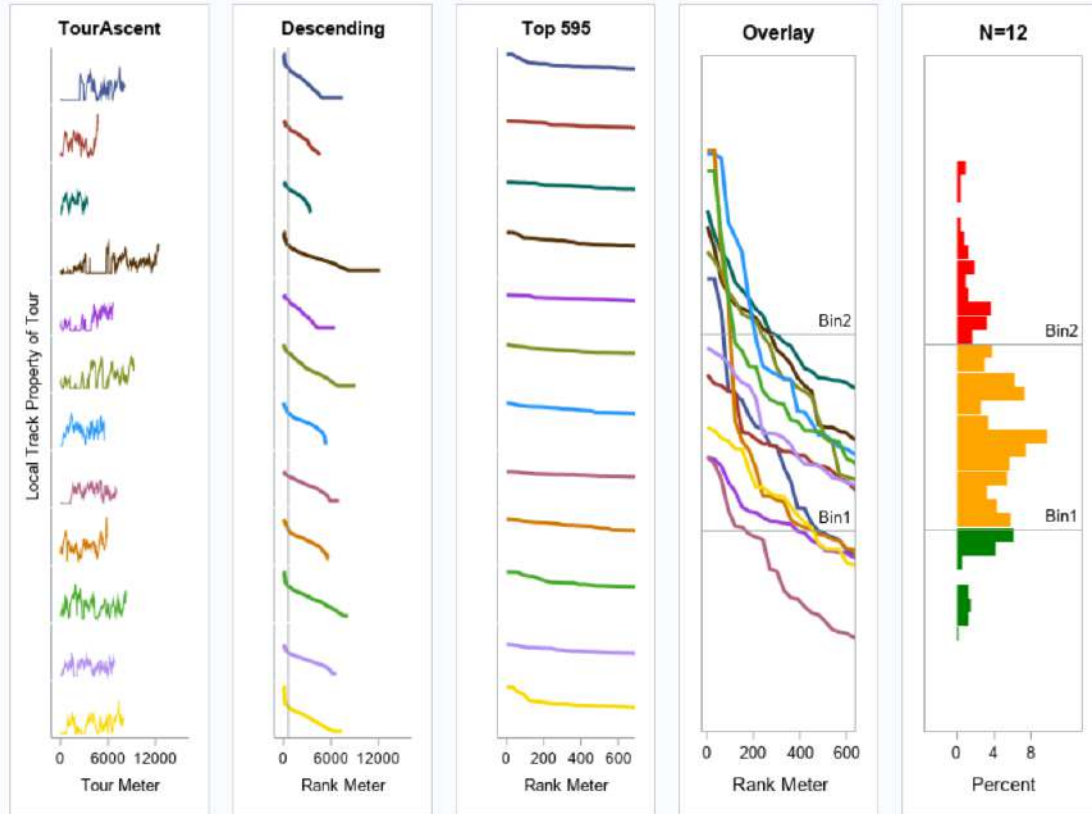
Data preparation

from local track properties to unique tour features



Data preparation

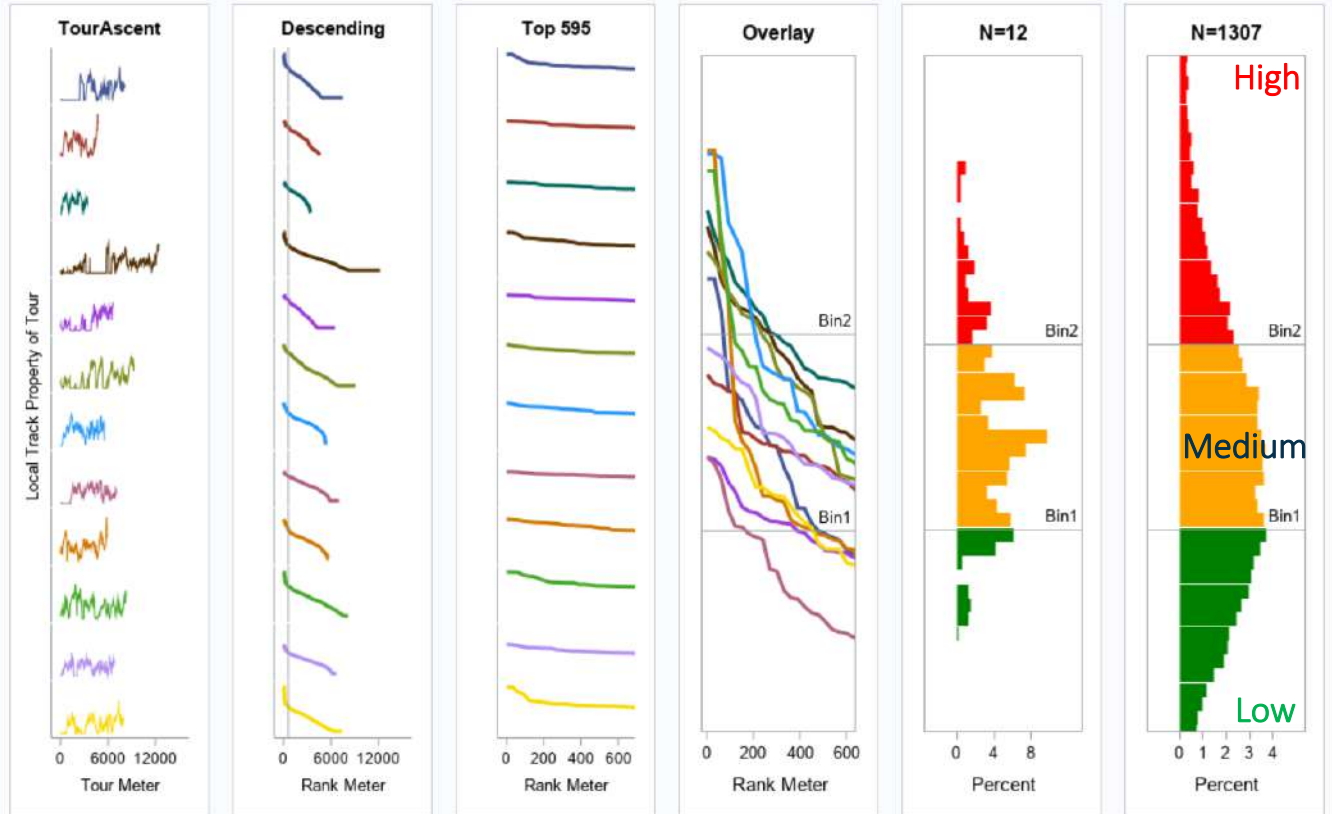
from local track properties to unique tour features



Local track properties of tours processed: Risk, Slope Angle, SpeedMax, Acceleration, Forestation, Curvature, Width,...

Data preparation

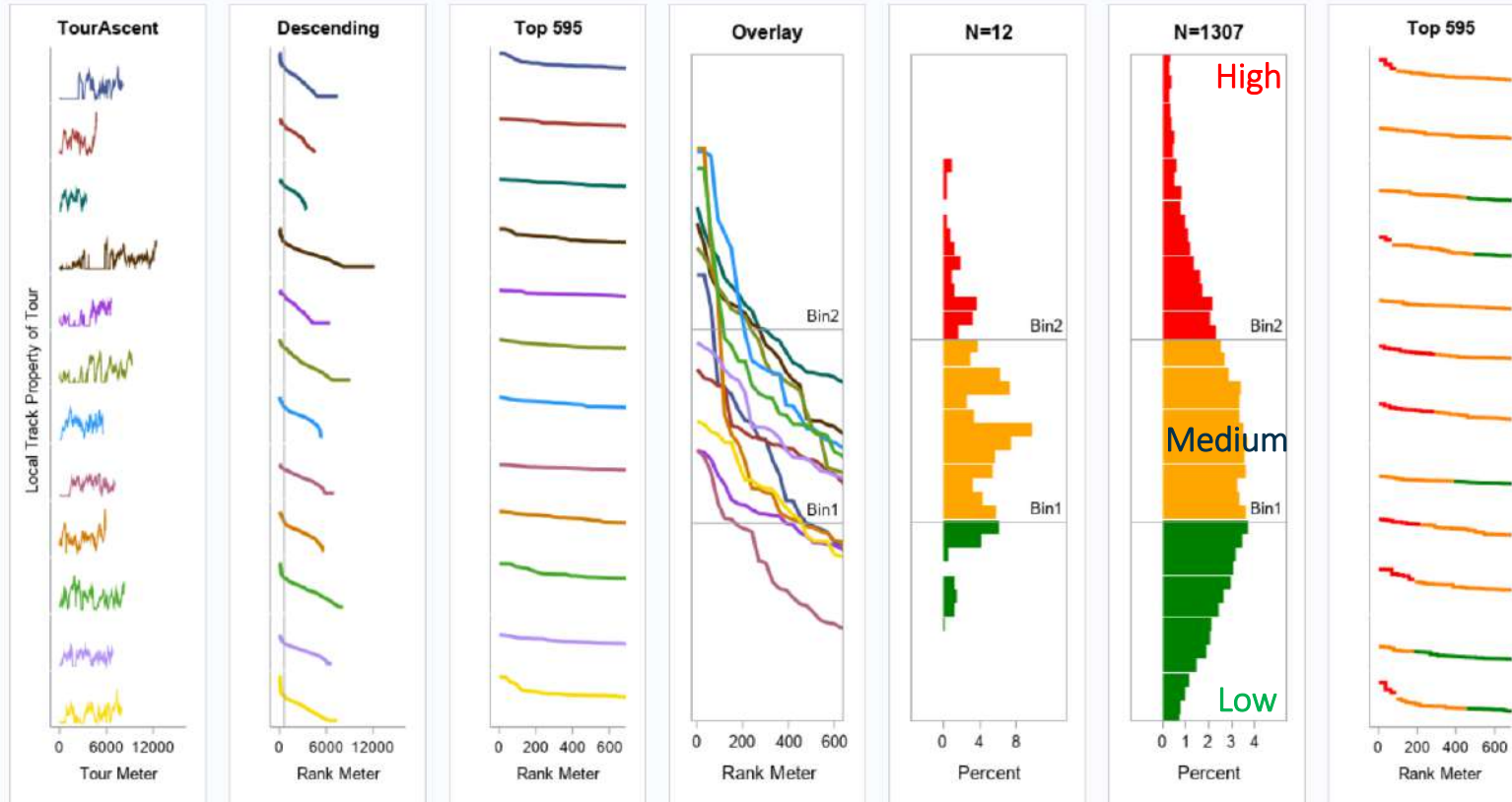
from local track properties to unique tour features



Local track properties of tours processed: Risk, Slope Angle, SpeedMax, Acceleration, Forestation, Curvature, Width,...

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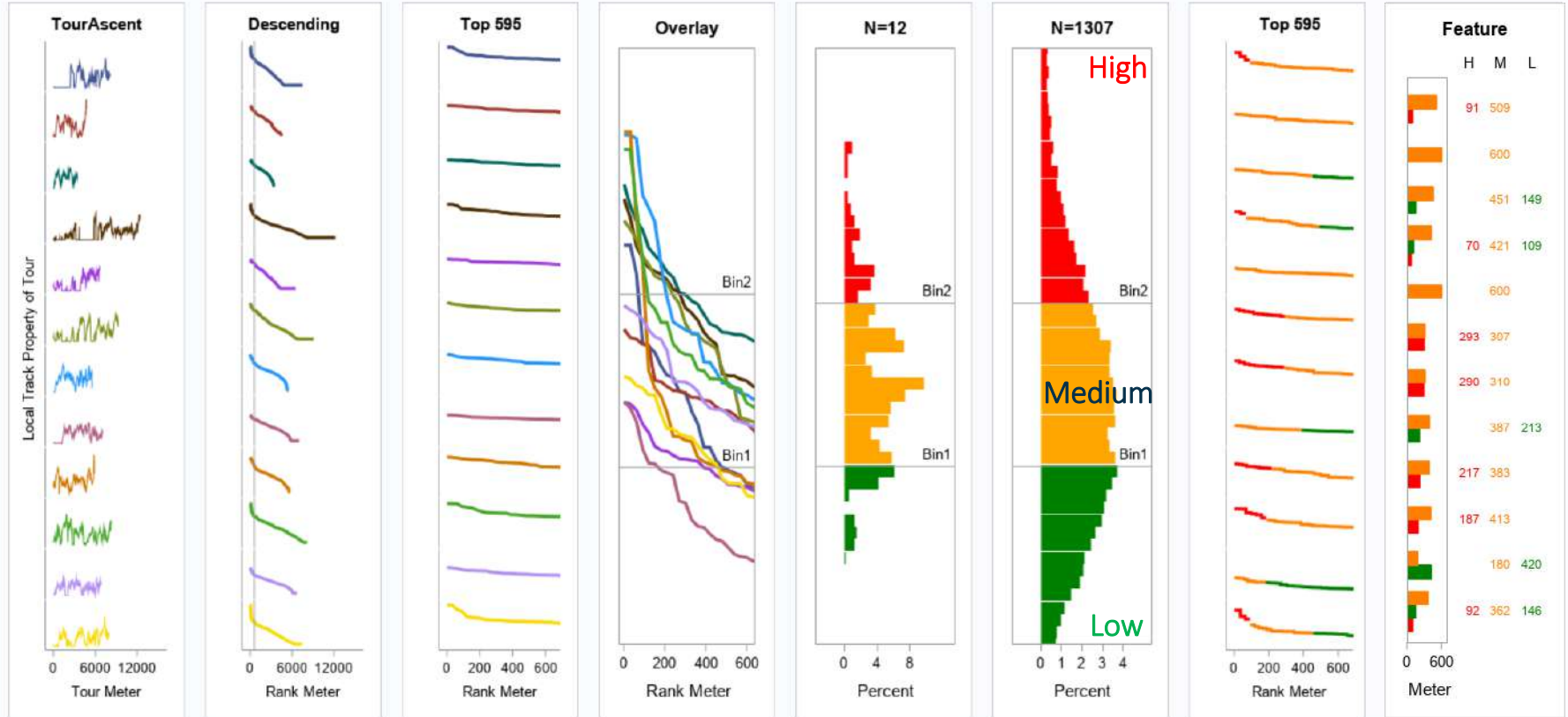
from local track properties to unique tour features



Local track properties of tours processed: Risk, Slope Angle, SpeedMax, Acceleration, Forestation, Curvature, Width,...

Data preparation

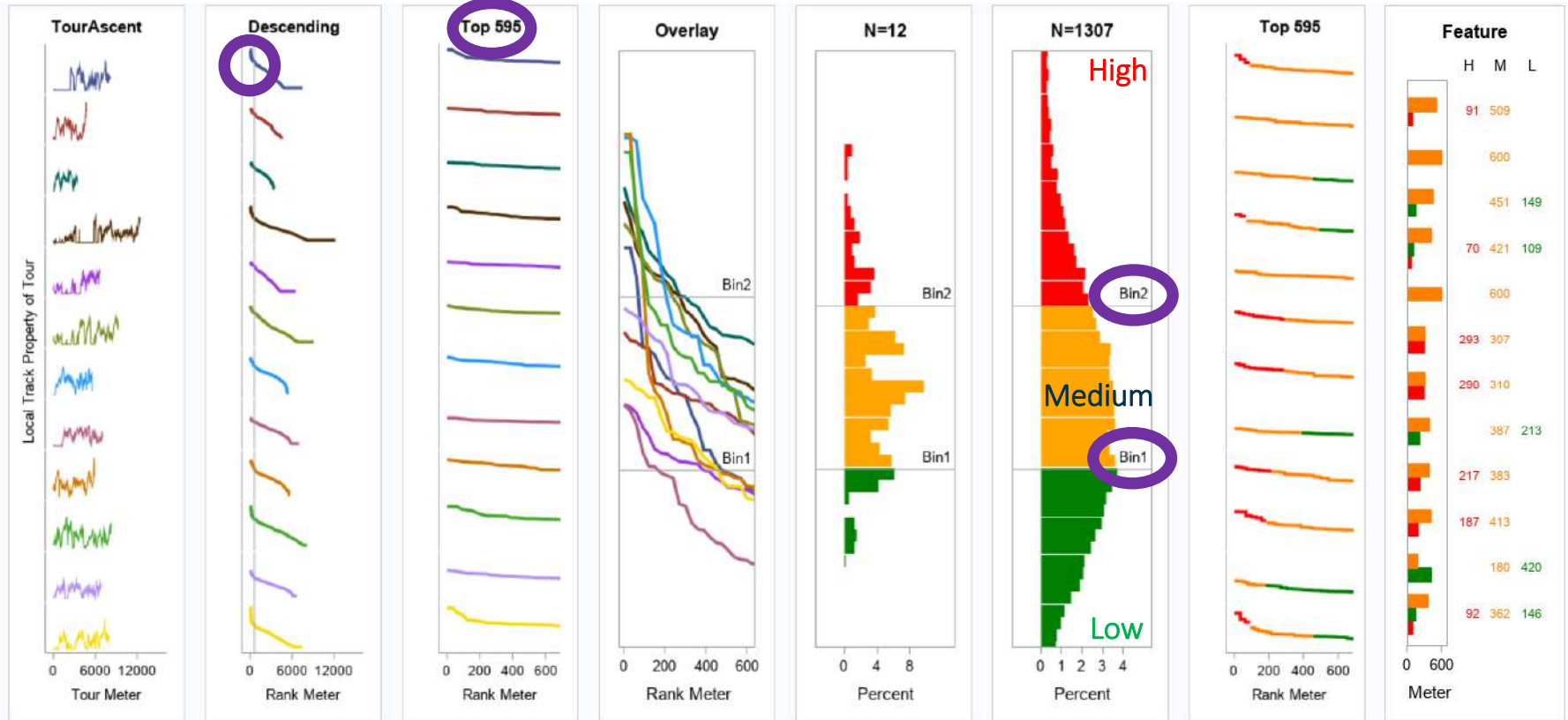
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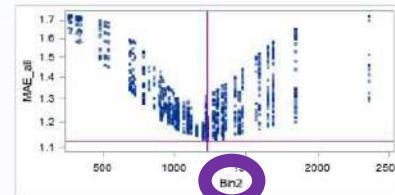
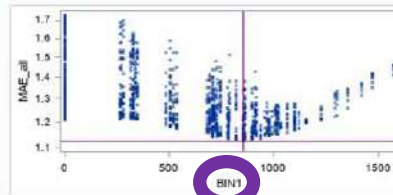
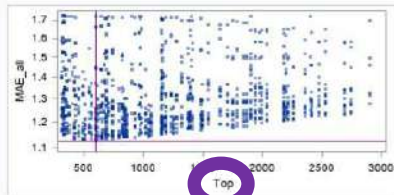
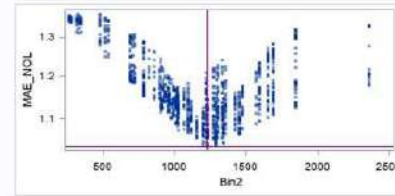
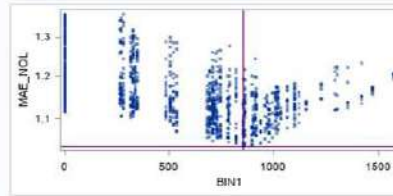
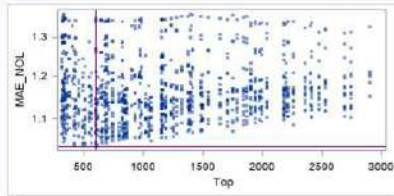
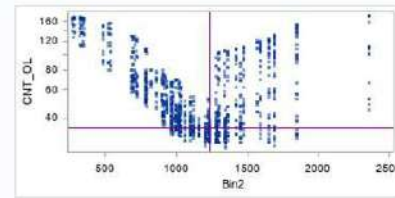
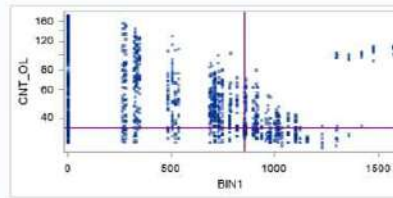
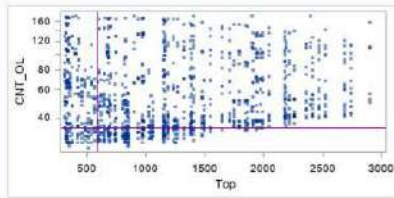


Local track properties of tours processed: Risk, Slope Angle, SpeedMax, Acceleration, Forestation, Curvature, Width,...

How to find good segmentation parameters: **Top, Bin1, Bin2** „Trial and Error“ minimizing Mean Absolute Prediction Error MAE

Optimal quantile regression model with best segmentation parameter TOP, BIN1, BIN2 (out of 5000 trials)

Top	BIN1	Bin2	Opt	MAE_all	MAE_NOL	CNT_OL	Intercept	RiskCnt_3	RiskCnt_3f	RiskCnt_2	RiskCnt_2f	SAC3_BEE_BEW_BVS_FRV	SAC3_TI	SAC3_ZS_GRN_GRS_GL_V
595	855	1229	*	1.12596	1.03841	35	1.83060	0.00866	0.00686	0.00464		-0.63060	0.67489	0



from 7 properties to 107 „best“ features

Sample of original local properties along the tour track

ID_Long	Meter	Speed	SlopeAngle	Forestation	Fold	Curvature	Acceleration	Width
1000_Sagliai..._PizZadrell	1	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	2	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	3	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	4	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	5	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	6	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	7	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	8	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	9	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	10	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	11	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	12	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	13	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	14	25	22.9	0.0	-15.45	-2.00	13	135
1000_Sagliai..._PizZadrell	15	25	23.0	0.0	-12.78	-5.53	13	147
1000_Sagliai..._PizZadrell	16	25	23.0	0.0	-12.78	-5.53	13	147
1000_Sagliai..._PizZadrell	17	25	23.0	0.0	-12.78	-5.53	13	147
1000_Sagliai..._PizZadrell	18	25	23.0	0.0	-12.78	-5.53	13	147
1000_Sagliai..._PizZadrell	19	25	23.0	0.0	-12.78	-5.53	13	147
1000_Sagliai..._PizZadrell	20	25	23.0	0.0	-12.78	-5.53	13	147
1000_Sagliai..._PizZadrell	21	25	23.0	0.0	-12.78	-5.53	13	147
1000_Sagliai..._PizZadrell	22	25	23.0	0.0	-12.78	-5.53	13	147
1000_Sagliai..._PizZadrell	23	25	23.0	0.0	-12.78	-5.53	13	147
1000_Sagliai..._PizZadrell	24	25	23.0	0.0	-12.78	-5.53	13	147

$$\sum x_{1\beta_t} \quad \sum x_{1\beta_t} \quad \sum x_{1\beta_t} \quad \sum x_{1\beta_t} \quad \sum x_{1\beta_t} \quad \sum x_{1\beta_t} \quad \sum x_{1\beta_t}$$



Final list of prediction feature candidates

VARNUM	NAME	VARNUM	NAME	VARNUM	NAME
1	TRN_VAL_Flag	36	ACCELS_L_Meter_Foot	72	FORESTSLOPE_L_Meter_Foot
2	Target_Difficulty	37	ACCELS_M_Meter_Foot	73	FORESTSLOPE_M_Meter_Foot
3	Id	38	ACCELS_H_Meter_Foot	74	FORESTSLOPE_H_Meter_Foot
4	Id_long	39	CURVN_L_Meter_Ski	75	RISK_L_Meter_Ski
5	lat	40	CURVN_M_Meter_Ski	76	RISK_M_Meter_Ski
6	x	41	CURVN_H_Meter_Ski	77	RISK_H_Meter_Ski
7	y	42	CURVN_L_Meter_Foot	78	RISK_L_Meter_Foot
8	z	43	CURVN_M_Meter_Foot	79	RISK_M_Meter_Foot
9	count_fm	44	CURVN_H_Meter_Foot	80	RISK_H_Meter_Foot
10	count_fm	45	CURVP_L_Meter_Ski	81	SLOPE_L_Meter_Ski
11	count_fm	46	CURVP_M_Meter_Ski	82	SLOPE_M_Meter_Ski
12	start	47	CURVP_H_Meter_Ski	83	SLOPE_H_Meter_Ski
13	end	48	CURVP_L_Meter_Foot	84	SLOPE_L_Meter_Foot
14	StartEle	49	CURVP_M_Meter_Foot	85	SLOPE_M_Meter_Foot
15	StepEle	50	CURVP_H_Meter_Foot	86	SLOPE_H_Meter_Foot
16	Ele	51	FOLDN_L_Meter_Ski	87	SPEEDM_L_Meter_Ski
17	SAC	52	FOLDN_M_Meter_Ski	88	SPEEDM_M_Meter_Ski
18	SAC0	53	FOLDN_H_Meter_Ski	89	SPEEDM_H_Meter_Ski
19	SAC1	54	FOLDN_L_Meter_Foot	90	SPEEDM_L_Meter_Foot
20	SAC2	55	FOLDN_M_Meter_Foot	91	SPEEDM_M_Meter_Foot
21	SAC3	56	FOLDN_H_Meter_Foot	92	SPEEDM_H_Meter_Foot
22	ACCELM_L_Meter_Ski	57	FOLDP_L_Meter_Ski	93	SPEEDS_L_Meter_Ski
23	ACCELM_M_Meter_Ski	58	FOLDP_M_Meter_Ski	94	SPEEDS_M_Meter_Ski
24	ACCELM_H_Meter_Ski	59	FOLDP_H_Meter_Ski	95	SPEEDS_H_Meter_Ski
25	ACCELM_L_Meter_Foot	60	FOLDP_L_Meter_Foot	96	SPEEDS_L_Meter_Foot
26	ACCELM_M_Meter_Foot	61	FOLDP_M_Meter_Foot	97	SPEEDS_M_Meter_Foot
27	ACCELM_H_Meter_Foot	62	FOLDP_H_Meter_Foot	98	SPEEDS_H_Meter_Foot
28	SAC_Vol	63	FOREST_L_Meter_Ski	99	WIDTH_L_Meter_Ski
29	Meter	64	FOREST_M_Meter_Ski	100	WIDTH_M_Meter_Ski
30	Mood	65	FOREST_H_Meter_Ski	101	WIDTH_H_Meter_Ski
31	Outlyer_code	66	FOREST_L_Meter_Foot	102	WIDTH_L_Meter_Foot
32	Outlyer_Comment	67	FOREST_M_Meter_Foot	103	WIDTH_M_Meter_Foot
33	ACCELS_L_Meter_Ski	68	FOREST_H_Meter_Foot	104	WIDTH_H_Meter_Foot
34	ACCELS_M_Meter_Ski	69	FORESTSLOPE_L_Meter_Ski	105	Author_Grp_Bias
35	ACCELS_H_Meter_Ski	70	FORESTSLOPE_M_Meter_Ski	106	SelectionProb
		71	FORESTSLOPE_H_Meter_Ski	107	SamplingWeight

Counting your steps like the fitness app of your smart phone

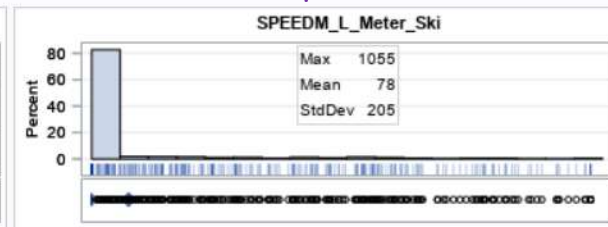
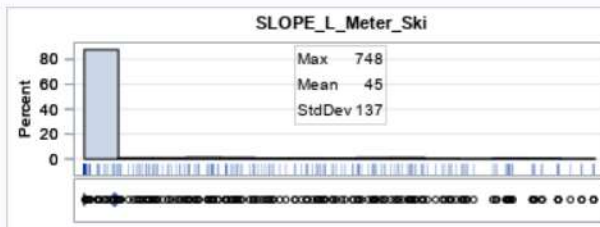


Risk

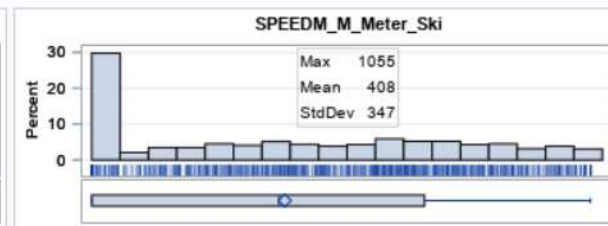
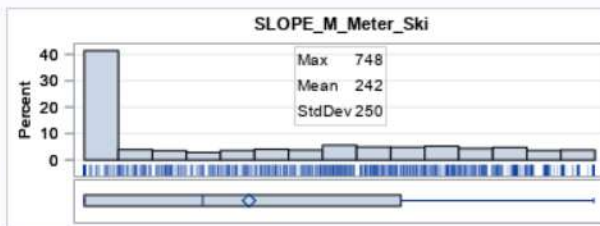
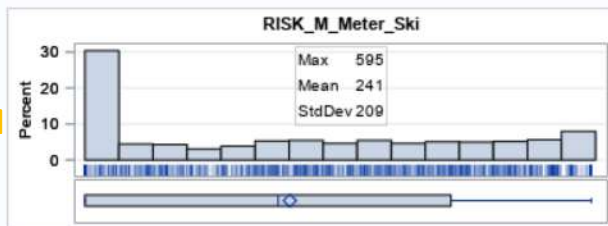
Slope

SpeedM

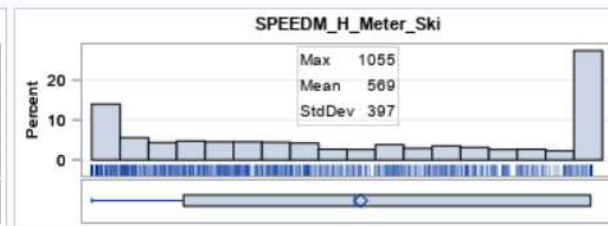
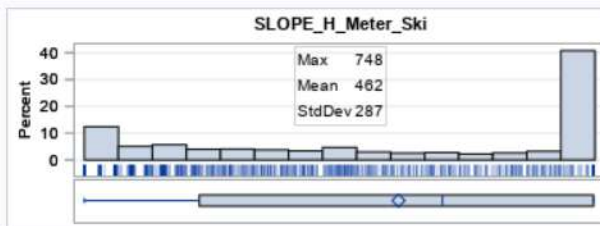
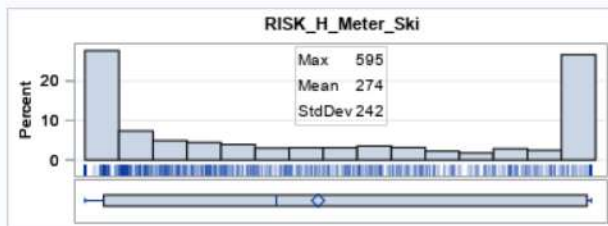
L



M

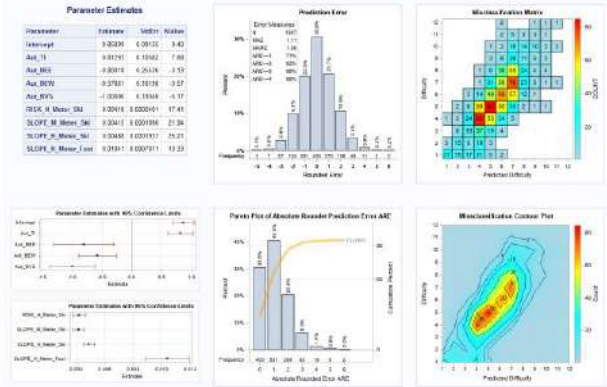
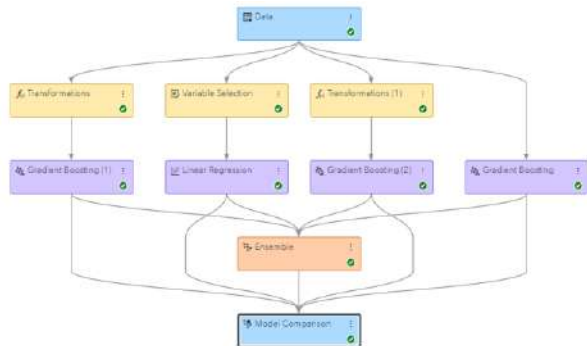


H



What predictive modeling approach did we take?

Machine Learning vs. Statistical Model

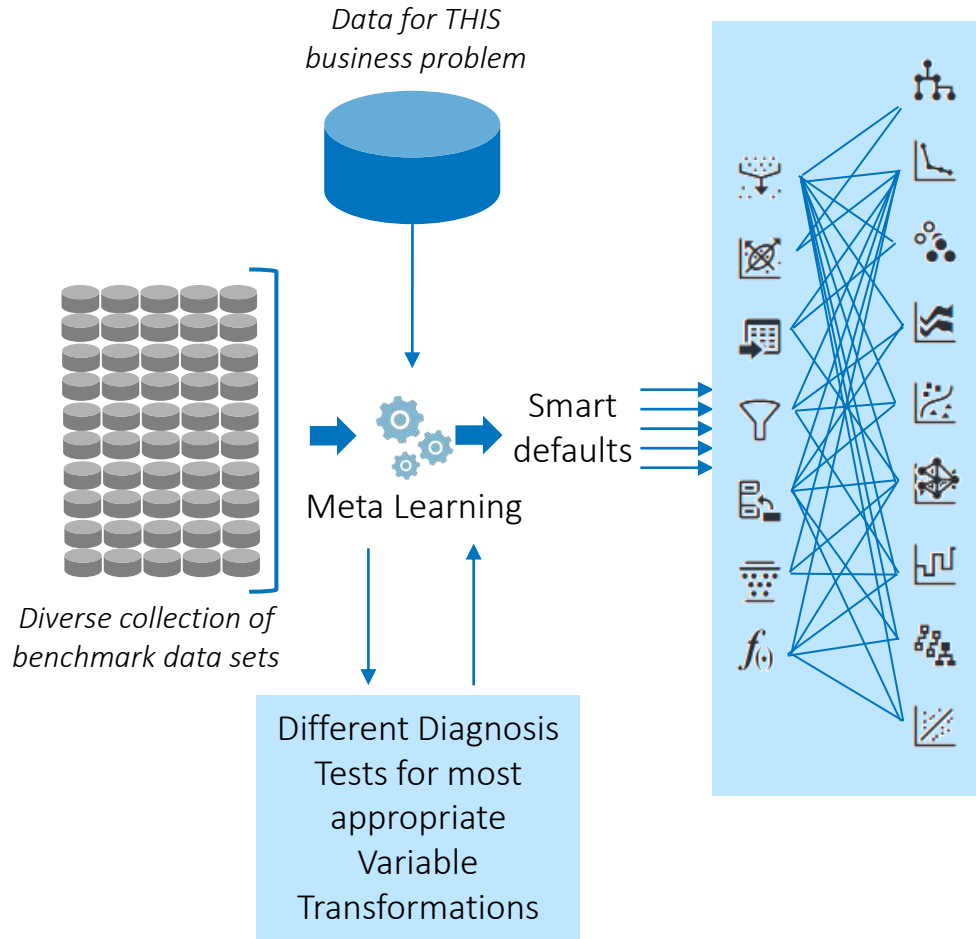


Final list of predictor feature candidates

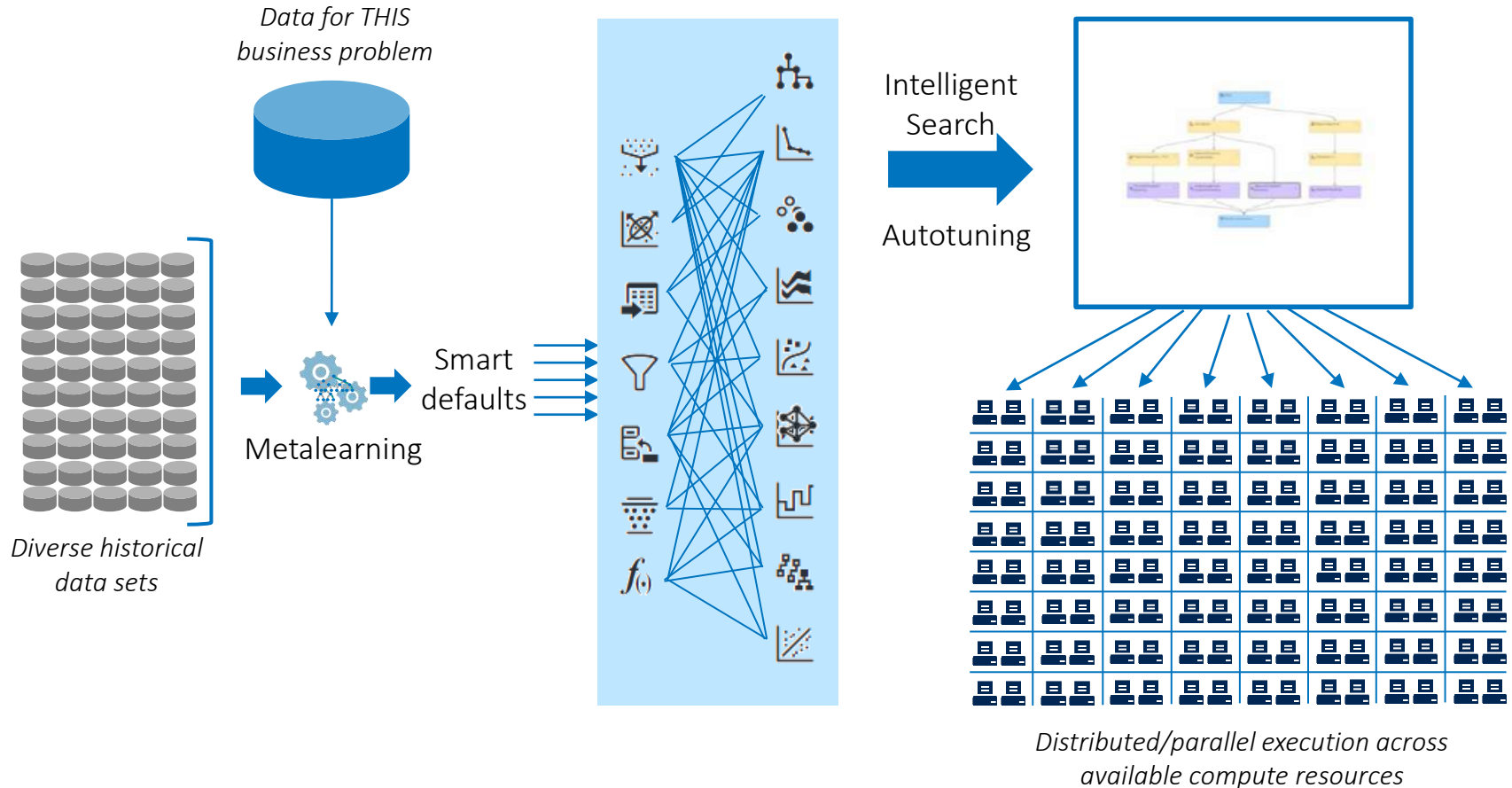
Variable	Model	Variable	Model	Variable	Model
1	AGE_18	27	AGE_25to29	54	AGE_25to29
2	AGE_20	28	AGE_20to24	55	AGE_20to24
3	AGE_20to24	29	AGE_25to29	56	AGE_25to29
4	AGE_25to29	30	AGE_20to24	57	AGE_20to24
5	AGE_25to29	31	AGE_25to29	58	AGE_25to29
6	AGE_25to29	32	AGE_25to29	59	AGE_25to29
7	AGE_25to29	33	AGE_25to29	60	AGE_25to29
8	AGE_25to29	34	AGE_25to29	61	AGE_25to29
9	AGE_25to29	35	AGE_25to29	62	AGE_25to29
10	AGE_25to29	36	AGE_25to29	63	AGE_25to29
11	AGE_25to29	37	AGE_25to29	64	AGE_25to29
12	AGE_25to29	38	AGE_25to29	65	AGE_25to29
13	AGE_25to29	39	AGE_25to29	66	AGE_25to29
14	AGE_25to29	40	AGE_25to29	67	AGE_25to29
15	AGE_25to29	41	AGE_25to29	68	AGE_25to29
16	AGE_25to29	42	AGE_25to29	69	AGE_25to29
17	AGE_25to29	43	AGE_25to29	70	AGE_25to29
18	AGE_25to29	44	AGE_25to29	71	AGE_25to29
19	AGE_25to29	45	AGE_25to29	72	AGE_25to29
20	AGE_25to29	46	AGE_25to29	73	AGE_25to29
21	AGE_25to29	47	AGE_25to29	74	AGE_25to29
22	AGE_25to29	48	AGE_25to29	75	AGE_25to29
23	AGE_25to29	49	AGE_25to29	76	AGE_25to29
24	AGE_25to29	50	AGE_25to29	77	AGE_25to29
25	AGE_25to29	51	AGE_25to29	78	AGE_25to29
26	AGE_25to29	52	AGE_25to29	79	AGE_25to29
27	AGE_25to29	53	AGE_25to29	80	AGE_25to29
28	AGE_25to29	54	AGE_25to29	81	AGE_25to29
29	AGE_25to29	55	AGE_25to29	82	AGE_25to29
30	AGE_25to29	56	AGE_25to29	83	AGE_25to29
31	AGE_25to29	57	AGE_25to29	84	AGE_25to29
32	AGE_25to29	58	AGE_25to29	85	AGE_25to29
33	AGE_25to29	59	AGE_25to29	86	AGE_25to29
34	AGE_25to29	60	AGE_25to29	87	AGE_25to29
35	AGE_25to29	61	AGE_25to29	88	AGE_25to29
36	AGE_25to29	62	AGE_25to29	89	AGE_25to29
37	AGE_25to29	63	AGE_25to29	90	AGE_25to29
38	AGE_25to29	64	AGE_25to29	91	AGE_25to29
39	AGE_25to29	65	AGE_25to29	92	AGE_25to29
40	AGE_25to29	66	AGE_25to29	93	AGE_25to29
41	AGE_25to29	67	AGE_25to29	94	AGE_25to29
42	AGE_25to29	68	AGE_25to29	95	AGE_25to29
43	AGE_25to29	69	AGE_25to29	96	AGE_25to29
44	AGE_25to29	70	AGE_25to29	97	AGE_25to29
45	AGE_25to29	71	AGE_25to29	98	AGE_25to29
46	AGE_25to29	72	AGE_25to29	99	AGE_25to29
47	AGE_25to29	73	AGE_25to29	100	AGE_25to29
48	AGE_25to29	74	AGE_25to29	101	AGE_25to29
49	AGE_25to29	75	AGE_25to29	102	AGE_25to29
50	AGE_25to29	76	AGE_25to29	103	AGE_25to29
51	AGE_25to29	77	AGE_25to29	104	AGE_25to29
52	AGE_25to29	78	AGE_25to29	105	AGE_25to29
53	AGE_25to29	79	AGE_25to29	106	AGE_25to29
54	AGE_25to29	80	AGE_25to29	107	AGE_25to29
55	AGE_25to29	81	AGE_25to29	108	AGE_25to29
56	AGE_25to29	82	AGE_25to29	109	AGE_25to29
57	AGE_25to29	83	AGE_25to29	110	AGE_25to29
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62	AGE_25to29	88	AGE_25to29	115	AGE_25to29
63	AGE_25to29	89	AGE_25to29	116	AGE_25to29
64	AGE_25to29	90	AGE_25to29	117	AGE_25to29
65	AGE_25to29	91	AGE_25to29	118	AGE_25to29
66	AGE_25to29	92	AGE_25to29	119	AGE_25to29
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71	AGE_25to29	97	AGE_25to29	124	AGE_25to29
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73	AGE_25to29	99	AGE_25to29	126	AGE_25to29
74	AGE_25to29	100	AGE_25to29	127	AGE_25to29
75	AGE_25to29	101	AGE_25to29	128	AGE_25to29
76	AGE_25to29	102	AGE_25to29	129	AGE_25to29
77	AGE_25to29	103	AGE_25to29	130	AGE_25to29
78	AGE_25to29	104	AGE_25to29	131	AGE_25to29
79	AGE_25to29	105	AGE_25to29	132	AGE_25to29
80	AGE_25to29	106	AGE_25to29	133	AGE_25to29
81	AGE_25to29	107	AGE_25to29	134	AGE_25to29
82	AGE_25to29	108	AGE_25to29	135	AGE_25to29
83	AGE_25to29	109	AGE_25to29	136	AGE_25to29
84	AGE_25to29	110	AGE_25to29	137	AGE_25to29
85	AGE_25to29	111	AGE_25to29	138	AGE_25to29
86	AGE_25to29	112	AGE_25to29	139	AGE_25to29
87	AGE_25to29	113	AGE_25to29	140	AGE_25to29
88	AGE_25to29	114	AGE_25to29	141	AGE_25to29
89	AGE_25to29	115	AGE_25to29	142	AGE_25to29
90	AGE_25to29	116	AGE_25to29	143	AGE_25to29
91	AGE_25to29	117	AGE_25to29	144	AGE_25to29
92	AGE_25to29	118	AGE_25to29	145	AGE_25to29
93	AGE_25to29	119	AGE_25to29	146	AGE_25to29
94	AGE_25to29	120	AGE_25to29	147	AGE_25to29
95	AGE_25to29	121	AGE_25to29	148	AGE_25to29
96	AGE_25to29	122	AGE_25to29	149	AGE_25to29
97	AGE_25to29	123	AGE_25to29	150	AGE_25to29
98	AGE_25to29	124	AGE_25to29	151	AGE_25to29
99	AGE_25to29	125	AGE_25to29	152	AGE_25to29



Data Science Pilot Action

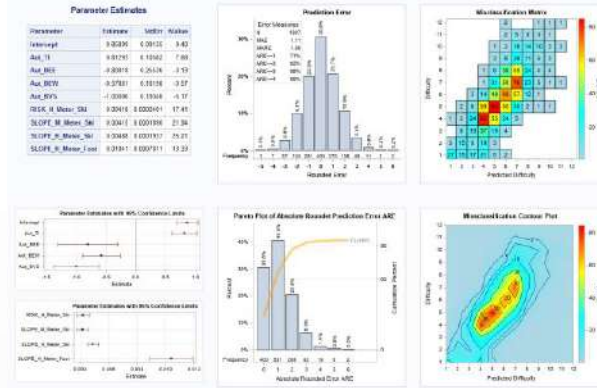
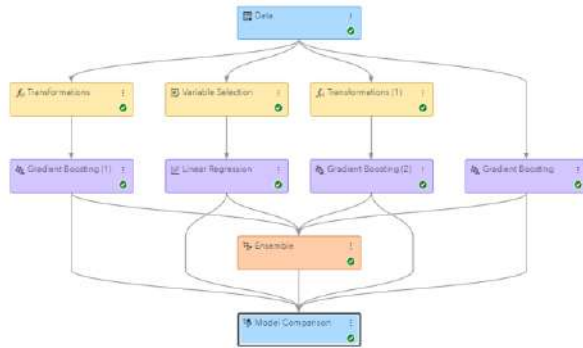


Data Science Pilot Action



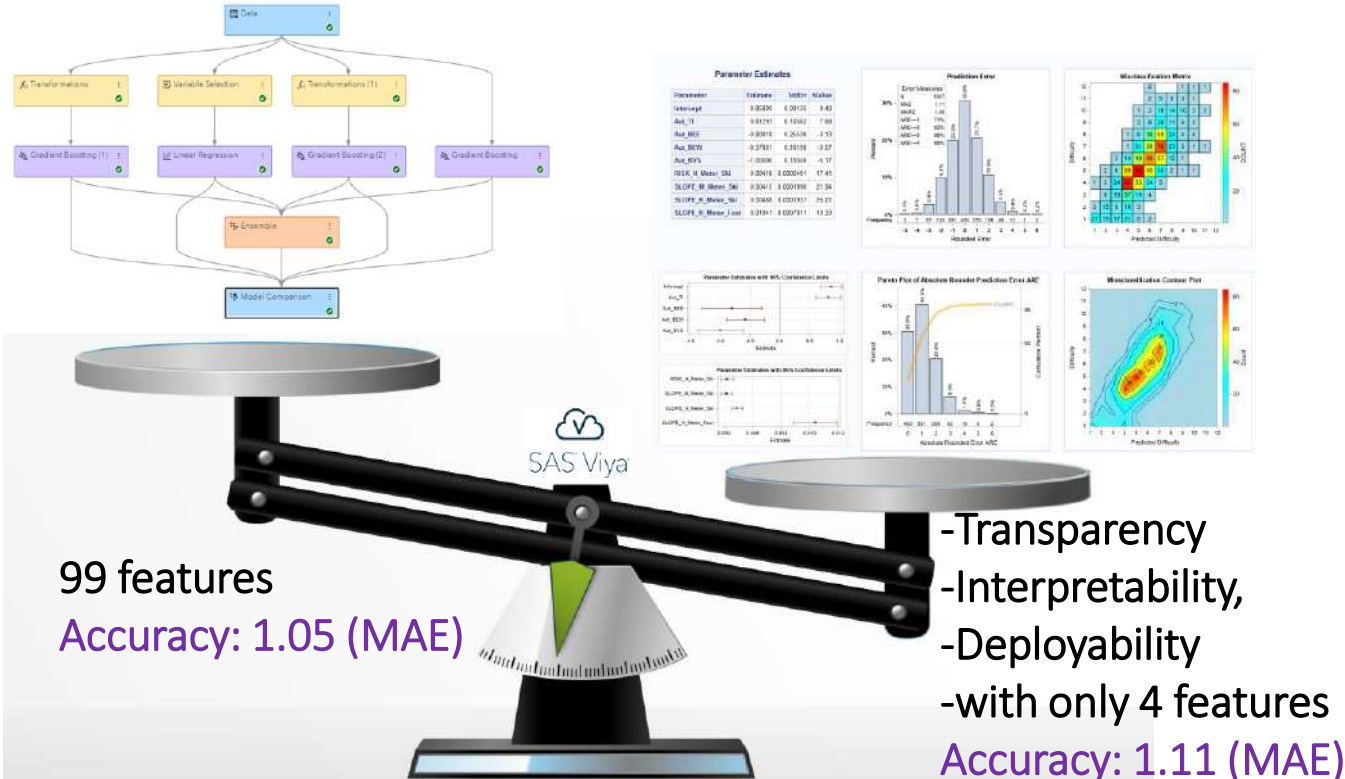
What predictive modeling approach did we take?

Machine Learning vs. Statistical Model



What Results did we get?

Transparency, Interpretability, Deployability outweighed Accuracy



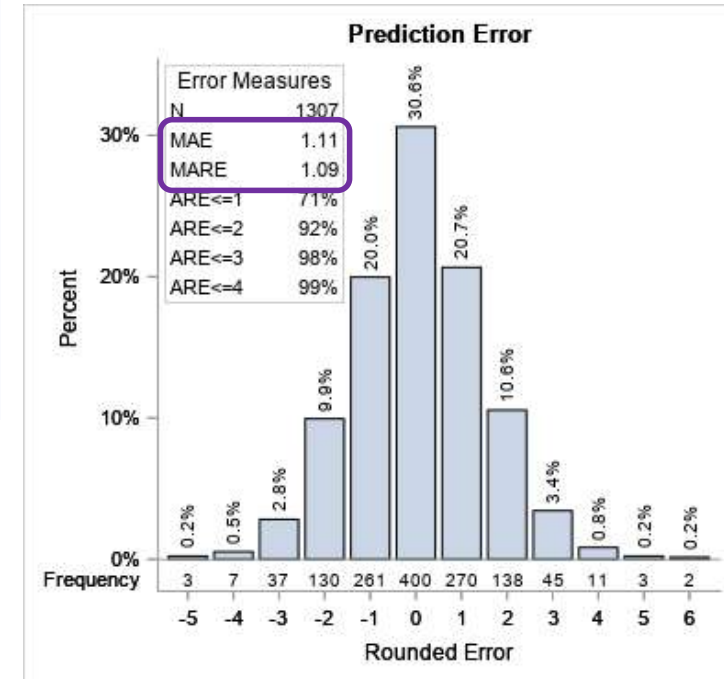
Variable selection with quantile regression

For median of difficulty

The HPQUANTSELECT Procedure
Quantile Level = 0.5

Selection Summary				
Step	Effect Entered	Number Effects In	AIC	SBC
0	Intercept	1	-185.5716	-180.3961
1	RISK_H_Meter_Ski	2	-984.6951	-974.3442
2	SLOPE_H_Meter_Foot	3	-1216.9940	-1201.4675
3	Aut_BVS	4	-1246.9930	-1226.2911
4	Aut_BEW	5	-1277.7180	-1251.8405
5	SLOPE_H_Meter_Ski	6	-1307.2939	-1276.2410
6	SLOPE_M_Meter_Ski	7	-1484.6233	-1448.3949
7	Aut_TI	8	-1510.2989	-1468.8950
8	Aut_BEE	9	-1522.1704*	-1475.5910*

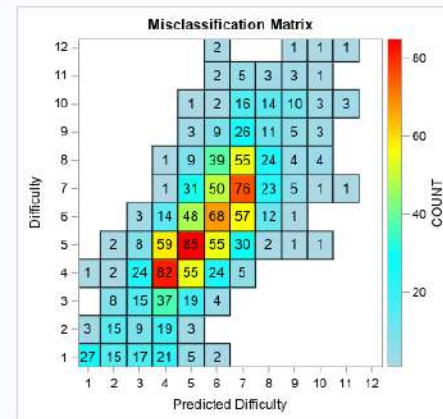
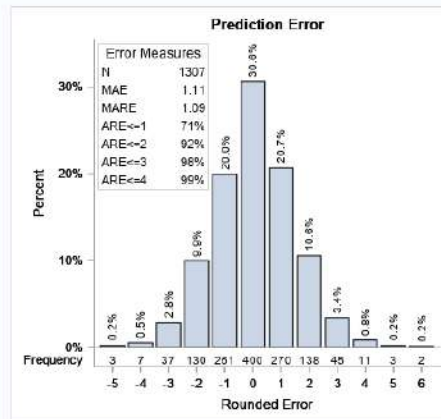
Fit Statistics	
Objective Function	725.08515
R1	0.40396
Adj R1	0.40028
AIC	-1522.17042
AICC	-1522.03163
SBC	-1475.59101
ACL	0.55477



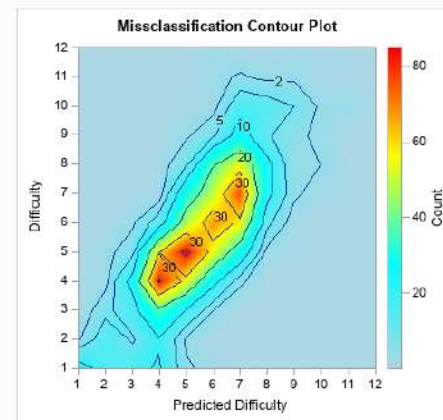
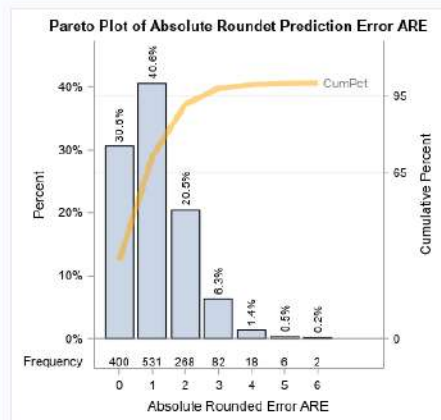
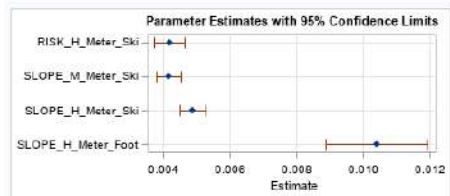
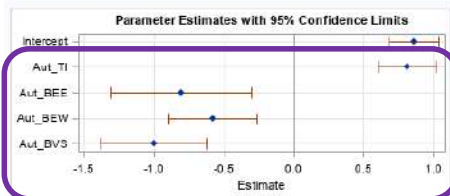
Risk:=SlopeAngle*SpeedMax

Parameter Estimates

Parameter	Estimate	StdErr	tValue
Intercept	0.85899	0.09135	9.40
Aut_TI	0.81293	0.10582	7.68
Aut_BEE	-0.80018	0.25536	-3.13
Aut_BEW	-0.57861	0.16198	-3.57
Aut_BVS	-1.00000	0.19346	-5.17
RISK_H_Meter_Ski	0.00418	0.0002401	17.41
SLOPE_M_Meter_Ski	0.00415	0.0001890	21.94
SLOPE_H_Meter_Ski	0.00488	0.0001937	25.21
SLOPE_H_Meter_Foot	0.01041	0.0007811	13.33



Four out of 12 selected author dummy variables



Significant author dummy variables

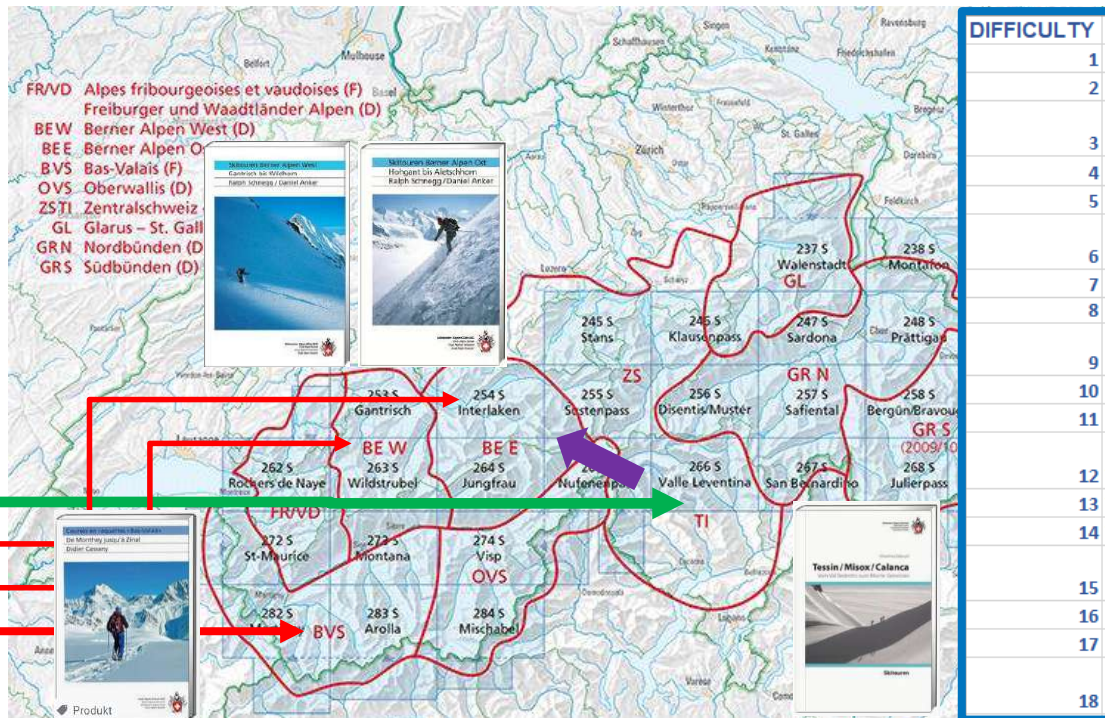
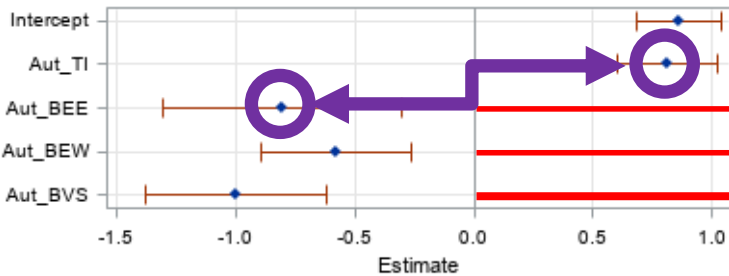
Systematic **O**verrating vs **U**nderrating bias detected for difficulty

Error Measures

N	1307
MAE	1.11
MARE	1.09
ARE<=1	71%
ARE<=2	92%
ARE<=3	98%
ARE<=4	99%

Parameter	Estimate	StdErr	tValue
Intercept	0.85899	0.09135	9.40
Aut_TI	0.81293	0.10582	7.68
Aut_BEE	-0.80018	0.25536	-3.13
Aut_BEW	-0.57861	0.16198	-3.57
Aut_BVS	-1.00000	0.19346	-5.17

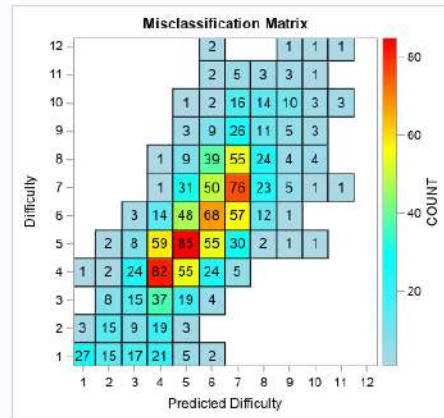
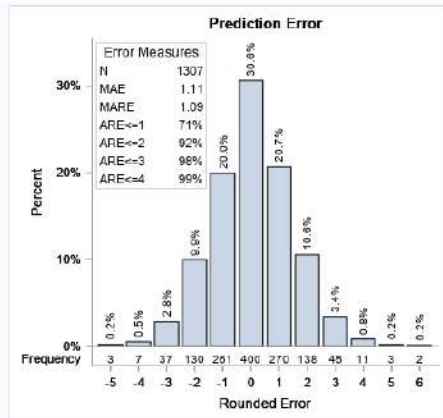
Parameter Estimates with 95% Confidence Limits



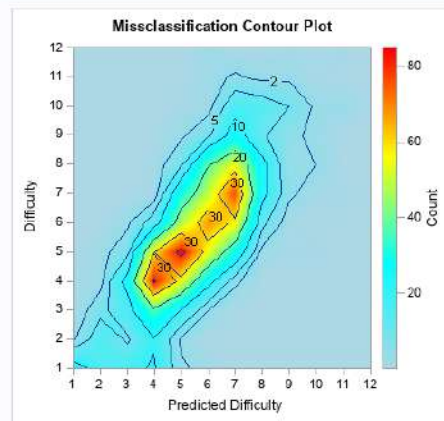
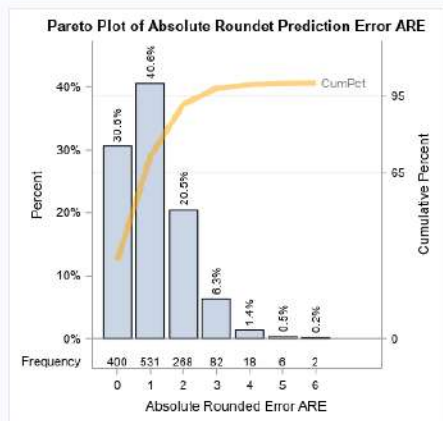
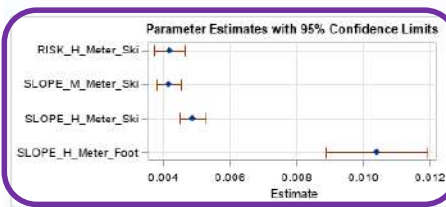
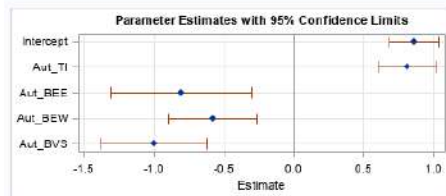
DIFFICULTY	
1	
2	
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17	
18	

Parameter Estimates

Parameter	Estimate	StdErr	tValue
Intercept	0.85899	0.09135	9.40
Aut_TI	0.81293	0.10582	7.68
Aut_BEE	-0.80018	0.25536	-3.13
Aut_BEW	-0.57861	0.16198	-3.57
Aut_BVS	-1.00000	0.19346	-5.17
RISK_H_Meter_Ski	0.00418	0.0002401	17.41
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SLOPE_H_Meter_Ski	0.00488	0.0001937	25.21
SLOPE_H_Meter_Foot	0.01041	0.0007811	13.33



Selected four out of ~20 000 ski tour features derived from local track properties

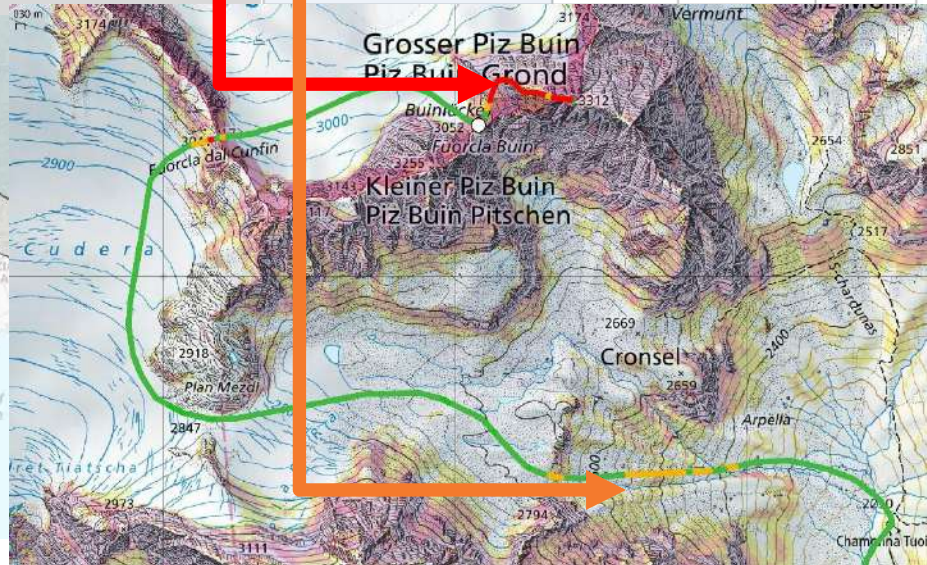
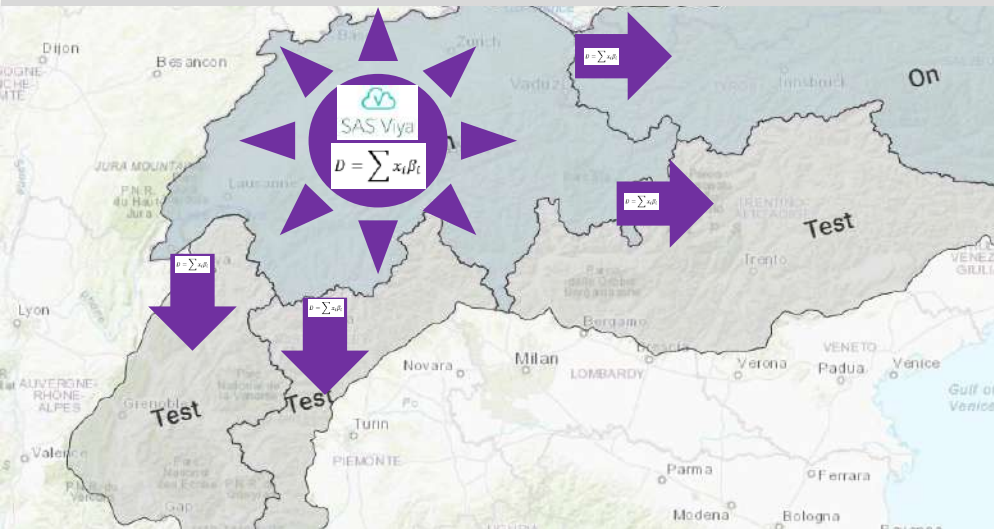


Model deployment to expand services of skitourenguru.ch to 4 neighboring countries with ~10 000 additional unrated ski tours



$$P_Difficulty = 0.859 + (418 * RISK_H_Meter_Ski + 415 * Slope_M_Meter_Ski + 488 * Slope_H_Meter_Ski + 1041 * Slope_H_Meter_Foot) / 100000$$

Parameter	Estimate	StdErr	tValue
Intercept	0.85899	0.09135	9.40
RISK_H_Meter_Ski	0.00418	0.0002401	17.41
SLOPE_M_Meter_Ski	0.00415	0.0001890	21.94
SLOPE_H_Meter_Ski	0.00488	0.0001937	25.21



Model Deployment and Integration



What's Skitourenguru

Skitourenguru supports you in the selection and planning of a suitable ski tour with low avalanche risk. For this purpose, Skitourenguru assigns daily an avalanche risk to thousands of ski tours in the alpine region:

Symbol	Values	Avalanche risk
▲	0-1	Low avalanche risk
▼	1-2	Elevated avalanche risk
●	2-3	High avalanche risk

In addition Skitourenguru marks static route cruxes with grey rings:

Symbol	Class	Meaning
○	1	Avalanche terrain
⊙	2	Typical avalanche terrain
⊗	3	Very typical avalanche terrain

On site and in the individual slope usually information becomes accessible that is not available to Skitourenguru. The information presented on Skitourenguru is subject to uncertainties (see Handbook). Therefore Skitourenguru must not be the only criterion to access a slope.

Choose a region

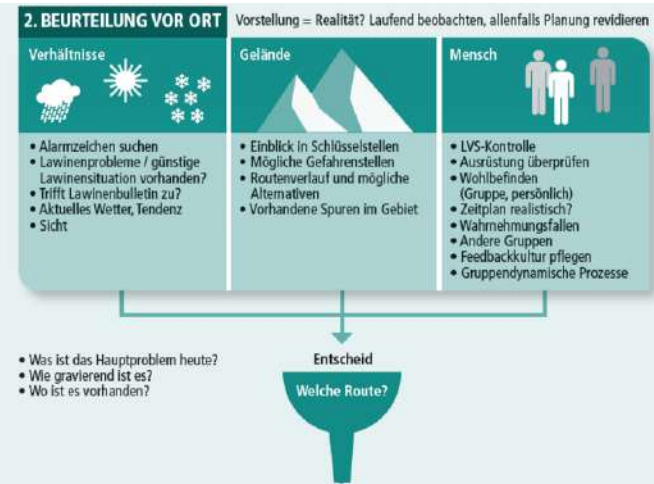
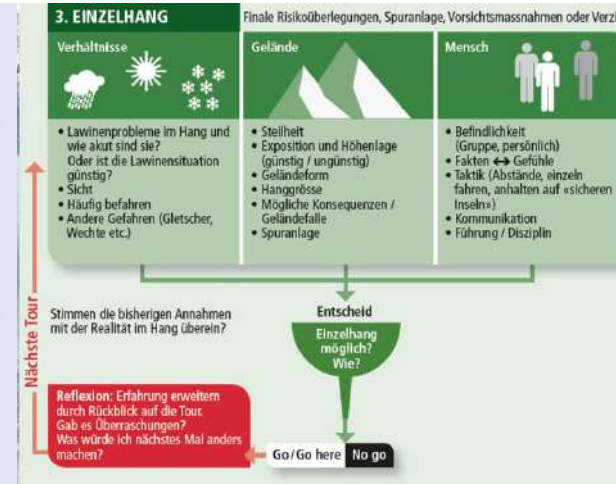
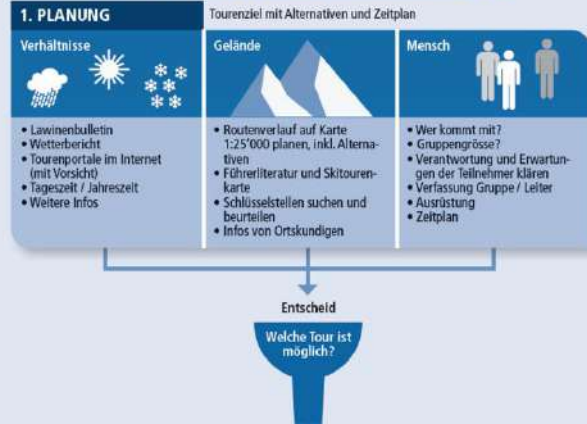
Region	State	Edition	Valid
Switzerland	On	17.30 h	16.4.2021-17.00 h
East Alps	On	18.30 h	16.4.2021-18.00 h
France	Test	16.30 h	16.4.2021-18.00 h
Nothwest-Italy	Test	16.30 h	16.4.2021-16.00 h
Notheast-Italy	Test	17.30 h	16.4.2021-16.00 h

Partners

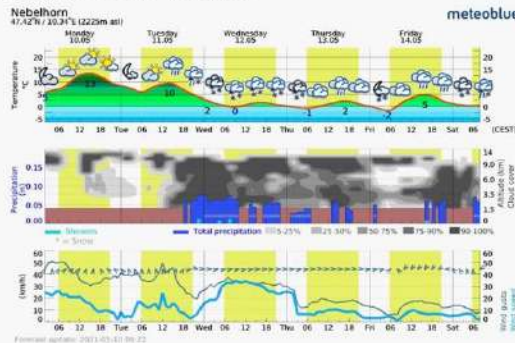
Skitourenguru is supported among others by the following partners:

Off course, skitourenguru does not exempt you from applying the recommended avalanche and risk assessment strategies

BEURTEILUNGS- UND ENTSCHEIDUNGSRAHMEN 3X3

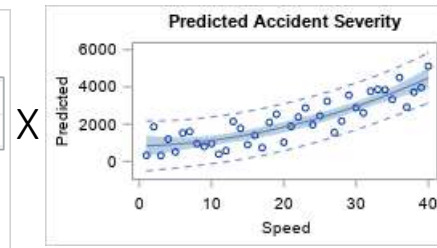
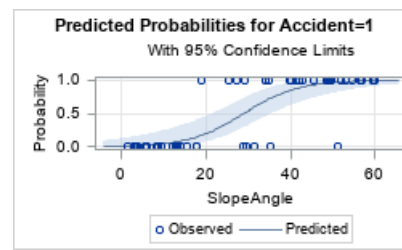


Meteogram - 5 days - Nebelhorn



Takeaways: What did we achieve?

Difficulty \sim



- We are proposing a new definition of **difficulty** metric derived from interaction of two local track properties: **slope angle and speed of falling** acting as proxies for accident probability and severity
- Overall, this metric is consistent with the unique human and cultural expertise published in the extensive SAC ski touring literature from which our model was trained.
- The discretionary range of the SAC methodology and prediction error margin is in the range of 1.1 to 1.8 levels of the 18-step SAC difficulty scale (i.e. “+” or “-”)
- An additional advantage of this methodology is its independent from prevailing weather and snow conditions at the moment of manual rating.
- We still have ongoing discussions with incorporation of the foot section in this model.
- The model provides the basis for fast and automatic bulk scoring prediction for up to ~ 10000 tours throughout the alps in AT, DE, IT, FR. It will support the expansion of Skitourenguru’s services.

DIFFICULTY	DIFFICULTY LABEL
1	Easy
2	Easy (+)
3	Less Difficult(-)
4	Less Difficult
5	Less Difficult (+)
6	Quite Difficult (-)
7	Quite Difficult
8	Quite Difficult (+)
9	Difficult (-)
10	Difficult
11	Difficult (+)
12	Very Difficult (-)
13	Very Difficult
14	Very Difficult (+)
15	Extremely Difficult (-)
16	Extremely Difficult
17	Extremely Difficult (+)
18	Extremely Difficult

Günter Schmudlach, Skitouren guru GmbH, Zürich CH



Ulrich Reincke, Principal Data Scientist, SAS, Heidelberg, DE



Thank you for your attention. And don't forget: Always put safety first



Example SAS Hackathon 2023

Productivity, Speed,
Fast, Reliable, Trustworthy , Fair Results without Bias

Timeline 2024

March - August



Prepare and recruit to the SAS Hackathon at SAS Innovate. Play the Ideation Game!

April - July



Engage and learn at the SAS Innovate and IOT on Tour Boot Camps/Sprint hacks.

April 16-19 Las Vegas
May - July IOT (TBD)

June - August



Kick off and registration.

June 1 - September 6

September - November



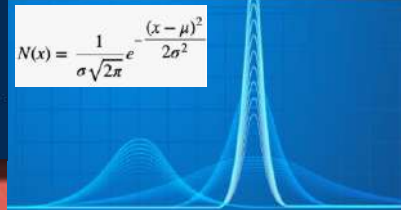
ONE month hack
September 16 - October 11

October 18-28 July
November 16 Awards

SAS Hackathons Sprints

Engage local customers in a half day hack. Manage by local Customer Advisory and Sales/Success Team. Data and use case provided by SAS. On customers infrastructure or provided cloud. Q2 Launch- 2024

The SAS Hackathon isn't a one-time event - it's a sprint within a marathon that spans several months.



1415 Persons Registered

140 Organizations

104 Teams to start

74 Countries

530 Active „Hackers“

72 Teams Completed

30 Calendar Days

19 Workdays

2 Video Submission per Team:

-3 Min Pitch Video

-10 Min Jury Video

Look at this year's innovative Use Cases and fantastic results

Address of Mentoring Special Snow Tigers in a Hackathon.pdf

OK OK, but what does it really mean: to mentor a Hackathon team?

I MENTOR CURIOUS MINDS.

HACKATHON >

#HackinSAS

The adventures of the Siberian Snow Tigers: a true story...

Outlier list with absolute prediction error gt 3.5

Type=Overrating

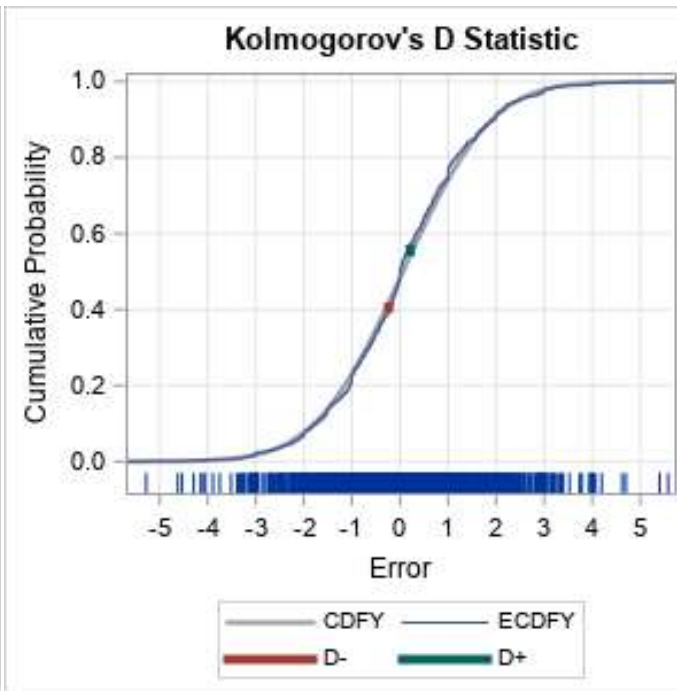
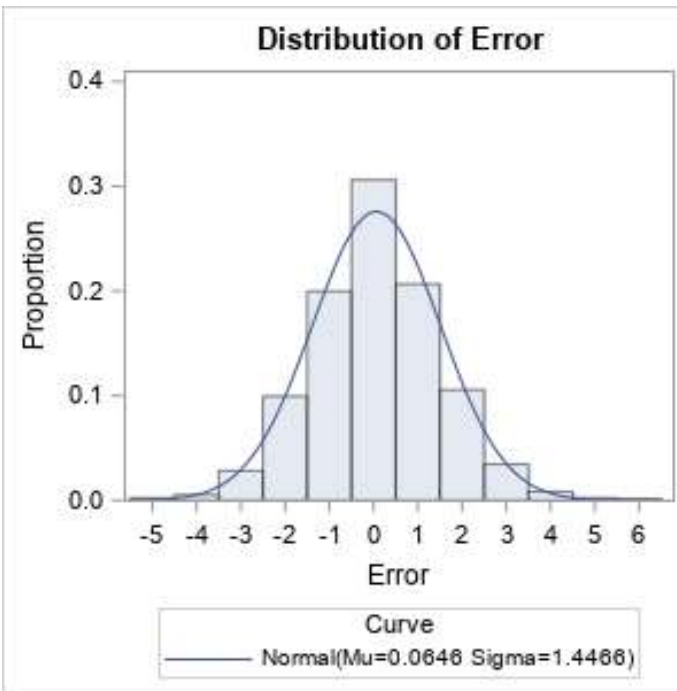
id_long	Difficulty	P	E	SAC0	Outlyer_Comment	StartEle	StopEle	Ele	RISK_H_Meter_Ski	SLOPE_H_Meter_Ski	SLOPE_M_Meter_Ski	SLOPE_H_Meter_Foot
1258_Hasen_Gotterli	1	5	-4	ZS		449	1394	945	0	748	0	0
171_Cons_PizTerri	7	11	-4	GRN		1468	3146	1789	595	748	0	360
564_Küblis_Chrüz	1	5	-4	GRN	Different Route	809	2190	1384	157	372	376	0
255_Furggels_Stelli	1	5	-4	GRN	Manual Underrat	1198	2047	976	147	643	105	0
912_Mühlebach_Ärnergale	1	5	-4	VSE	Different Route	1232	2621	1391	169	629	119	0
387_MittlerRossfal_Hochalp	1	5	-4	GL	Compromise	899	1527	650	234	264	484	0
535_Ladstafel_Mittaghorn	5	9	-4	VSE		1924	3004	1080	595	748	0	220
358_Latsch_CuolmdaLatsch	1	6	-5	GRS	Road above 1600	1609	2294	686	244	748	0	0
1035_HospizSimplonp_MonteLeone	5	10	-5	VSE		1998	3548	1657	508	698	50	290
1466_Sufers_VizanPintg	1	6	-5	GRN	Road above 1600	1413	2513	1120	423	748	0	0

Type=Underrating

id_long	Difficulty	P	E	SAC0	Outlyer_Comment	StartEle	StopEle	Ele	RISK_H_Meter_Ski	SLOPE_H_Meter_Ski	SLOPE_M_Meter_Ski	SLOPE_H_Meter_Foot
903_MayensdeMërib_PointedeVouasso	12	6	6	BVS		1728	3481	1755	595	748	0	0
367_ZurEich_GrosBrun	12	6	6	BEW	Compromise	951	2098	1147	595	748	0	0
1231_Engi_Gufelstock	11	6	5	GL	Compromise	812	2434	1622	260	748	0	0
706_ChantSura_PizRadönt	10	5	5	GRS	Other Ski Depot	2330	3056	751	28	120	147	300
407_Urnerboden_Läckistock	11	6	5	ZS	Compromise	1376	2483	1107	455	697	51	0
725_Dürrboden_Leidhorn	9	5	4	GRS	Compromise	2006	2930	925	150	292	456	0
507_H.d'Allières_VanildesArtses	11	7	4	FRV	Other Ski Depot	1006	1986	980	127	0	707	250
613_Diavolezza_PizCambrena	11	7	4	GRS		2978	3595	855	595	748	0	0
736_Brigels_Bifertenstock	11	7	4	GRN		1285	3416	2173	595	748	0	0
818_Jochstock_ReissendNollen	11	7	4	ZS		2508	3002	493	595	748	0	0
886_LeFlon_Chambairy	10	6	4	BVS		1046	2198	1151	595	748	0	0
916_BourgSt.Berna_MontVélan	10	6	4	BVS		1916	3721	1805	595	748	0	0
1448_Münster_Hejizwächte	9	5	4	BEE	Compromise	1387	3083	1696	323	748	0	0
1236_Elm_Grüenenspitz	9	5	4	GL	Other Ski Depot	960	2354	1394	94	316	432	60
1227_Horb_Frümsel	11	7	4	GL	Other Ski Depot	887	2261	1374	22	113	635	300
591_Tschlin_Muttler	8	4	4	GRS	Other Ski Depot	1533	3290	1758	44	22	726	30

Prediction Residuals / Error

Test for normality (N=1307)



Kolmogorov's D Statistic

The UNIVARIATE Procedure
Fitted Normal Distribution for Error

Goodness-of-Fit Tests for Normal Distribution

Test	Statistic	p Value
Kolmogorov-Smirnov D	0.03076998	Pr > D 0.168
Cramer-von Mises W-Sq	0.33496573	Pr > W-Sq 0.110
Anderson-Darling A-Sq	1.76279181	Pr > A-Sq 0.126

Kolmogorov's D Statistic

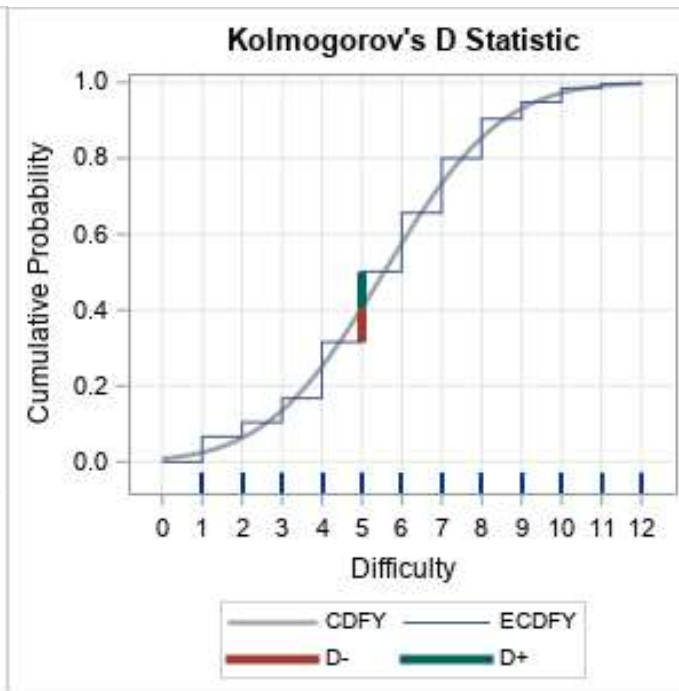
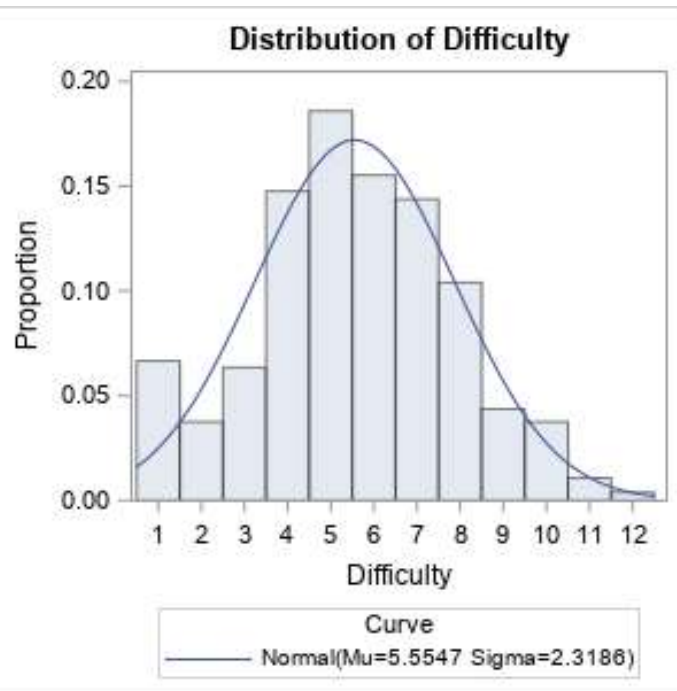
D
0.03077

Kolmogorov D

	Error	Value	Low	High
D-	-0.232248	0.0269607	0.3917368	0.4186975
D+	0.2099216	0.03077	0.5400028	0.5707728

Target Variable Difficulty

Test for normality (N=1307)



Kolmogorov's D Statistic

The UNIVARIATE Procedure
Fitted Normal Distribution for Difficulty (diff)

Goodness-of-Fit Tests for Normal Distribution

Test	Statistic	p Value
Kolmogorov-Smirnov	D 0.0956892	Pr > D <0.001
Cramer-von Mises	W-Sq 2.0483810	Pr > W-Sq <0.001
Anderson-Darling	A-Sq 11.8013910	Pr > A-Sq <0.001

Kolmogorov's D Statistic

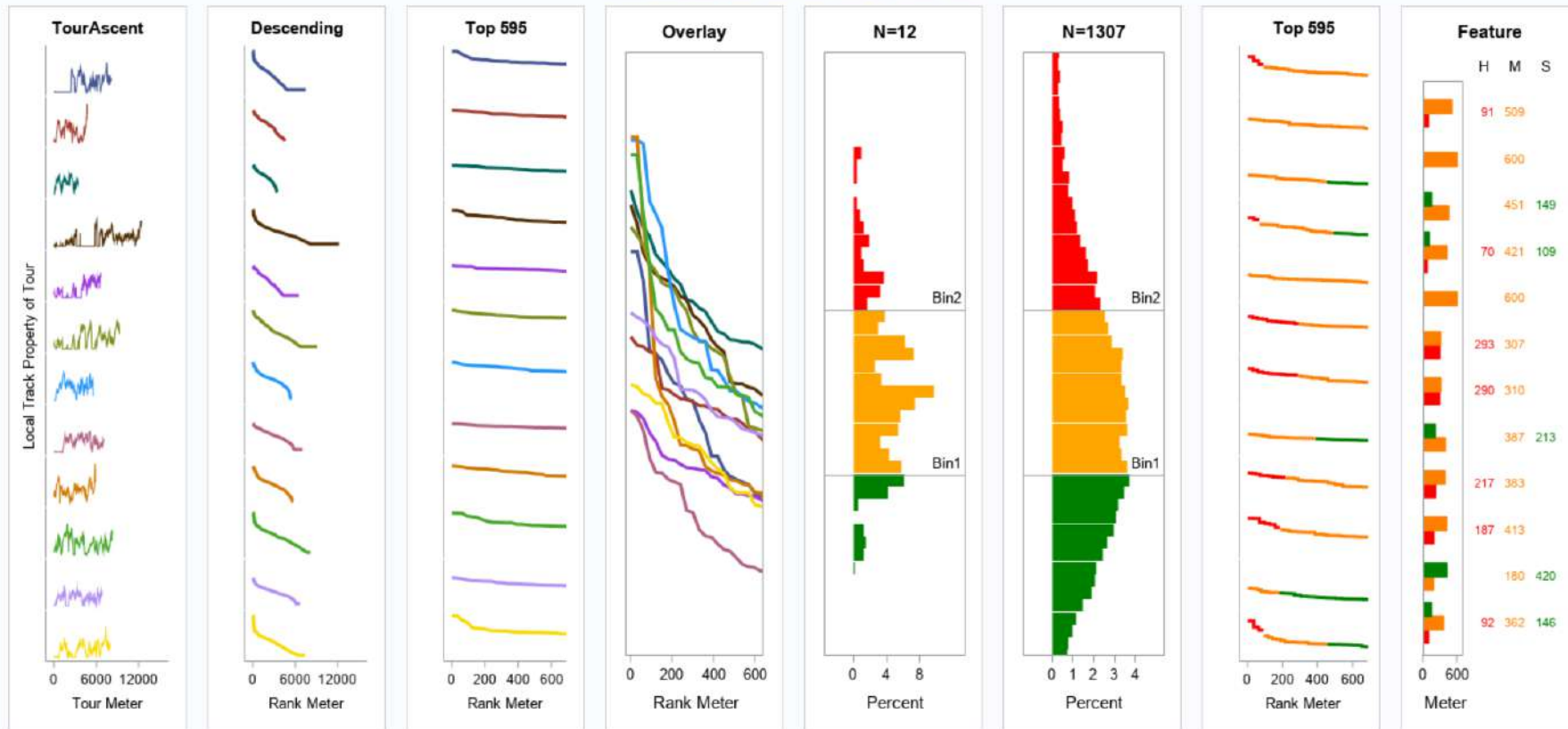
D
0.0956892

Kolmogorov D

	x	Value	Low	High
D-	5	0.0902327	0.3152257	0.4054584
D+	5	0.0956892	0.4054584	0.5011477

Data preparation: from properties to features

Illustrative example of local property along four tracks



Local track properties of tours processed: Risk, Slope Angle, SpeedMax, Acceleration, Forestation, Curvature, Width,...