Estimation of parameter importance and interaction with RF

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Below there is an example using ACOTSP:

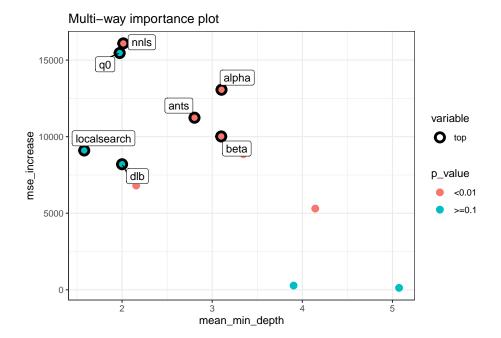
- 20 secs cut off time
- 11 parameters
- 200 instances of size 2000
- 5000 experiments for configuration

1. Configuration ranking as dependent variable

	variable	mean_min_depth	no_of_nodes	mse_increase	node_purity_increase	no_of_trees	times_a_root	p_value
9	localsearch	1.580000	11712	9099.0143	22939928	300	48	1
11	q0	1.973333	45043	15463.9853	59530677	300	88	1
5	dlb	2.000000	8965	8198.4909	18601123	300	38	1
10	nnls	2.013333	67056	16092.5830	50521182	300	18	0
1	algorithm	2.093333	17393	7626.4907	27977278	300	78	1
8	instance	2.156667	227931	6810.7911	85093917	300	0	0
3	ants	2.803333	84446	11238.2352	37397603	300	14	0
4	beta	3.100000	89000	10016.2334	40649159	300	0	0
2	alpha	3.103333	88859	13065.0803	45253707	300	5	0
13	rho	3.346667	84217	8860.2857	31832405	300	6	0
7	elitistants	3.903333	11005	276.6651	1364817	300	5	1
6	dummy	4.143333	66966	5302.7057	20237786	300	0	0
12	rasrank	5.073333	15798	126.5911	1929760	300	0	1

We can plot some measures using the randomForestExplainer package. In this case, since we are not predicting performance, analizing the importance of parameters not including the instance would be an error.

Warning: Using alpha for a discrete variable is not advised.



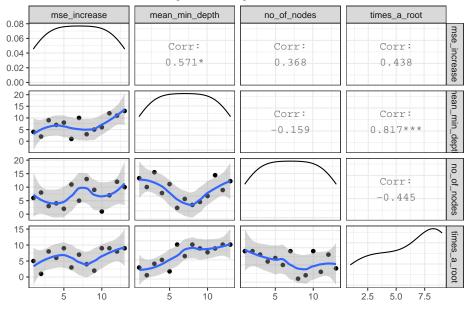
We can also visualize the relationship between importance measures

```
#plot_importance_ggpairs(importance_frame)
plot_importance_rankings(importance_frame, measures=c("mse_increase", "mean_min_depth", "no_of_nodes",

## `geom_smooth()` using formula 'y ~ x'

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```

Relations between rankings according to different measures



After the analysis of conditional parameters the most important 5 parameters are (plus reference added for

interaction analysis):

```
print(important_parameters)
```

We run the interaction analysis and find the importance of interactions:

```
kable(full_interactions_frame) %>% kable_styling(latex_options="scale_down")
```

			1		
variable	root_variable	mean_min_depth	occurrences	interaction	uncond_mean_min_depth
nnls	algorithm	0.9100719	278	algorithm:nnls	1.366667
algorithm	algorithm	1.3782254	274	algorithm:algorithm	1.310000
dummy	algorithm	0.9681535	274	algorithm:dummy	1.433333
nnls	dummy	0.8765468	270	dummy:nnls	1.366667
dummy	dummy	1.1423022	267	dummy:dummy	1.433333
nnls	localsearch	1.1505755	265	localsearch:nnls	1.366667
nnls	nnls	1.1925180	265	nnls:nnls	1.366667
localsearch	localsearch	1.7280576	258	localsearch:localsearch	1.403333
dummy	nnls	1.4168345	256	nnls:dummy	1.433333
dummy	localsearch	1.5509353	250	localsearch:dummy	1.433333
localsearch	algorithm	1.7513909	247	algorithm:localsearch	1.403333
algorithm	nnls	2.1723741	230	nnls:algorithm	1.310000
localsearch	nnls	2.4574101	224	nnls:localsearch	1.403333
algorithm	dummy	2.3841727	223	dummy:algorithm	1.310000
localsearch	dummy	2.4846043	221	dummy:localsearch	1.403333
algorithm	localsearch	2.5634532	216	localsearch:algorithm	1.310000

Once we filter dummy interactions and aggregate bidirectional interactions we get a matrix where the importance of interactions are summarized:

```
print(interactions_frame)
```

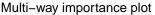
```
## variable root_variable mean_min_depth occurrences interaction
## 1 nnls algorithm 0.9100719 508 algorithm:nnls
## uncond_mean_min_depth
## 1 1.366667
```

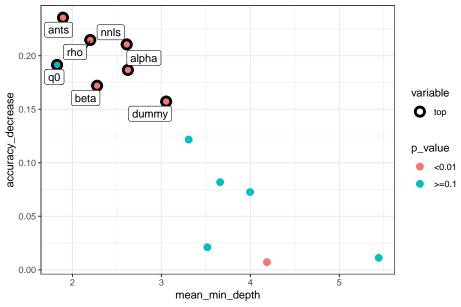
2. Configuration ranking quartile as dependent variable

	variable	mean_min_depth	no_of_nodes	accuracy_decrease	gini_decrease	no_of_trees	times_a_root	p_value
11	q0	1.826667	20875	0.1914654	744.2653	300	70	1
3	ants	1.893333	32935	0.2355764	1038.1176	300	50	0
13	rho	2.200000	32707	0.2146773	1035.0556	300	28	0
4	beta	2.276667	34873	0.1719534	1125.2795	300	13	0
10	nnls	2.610000	27377	0.2105706	854.9377	300	25	0
2	alpha	2.623333	34671	0.1866669	1104.9939	300	7	0
6	dummy	3.053333	25785	0.1571873	797.8111	300	4	0
1	algorithm	3.306667	7826	0.1216607	220.9197	300	55	1
12	rasrank	3.516667	6258	0.0210585	175.7423	300	5	1
5	dlb	3.660000	5230	0.0819014	148.2808	300	30	1
9	localsearch	3.996667	8358	0.0726623	235.1934	300	11	1
8	instance	4.186667	69848	0.0071969	1164.0060	300	0	0
7	elitistants	5.443333	4427	0.0111779	112.1926	300	2	1

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We can also visualize the relationship between importance measures

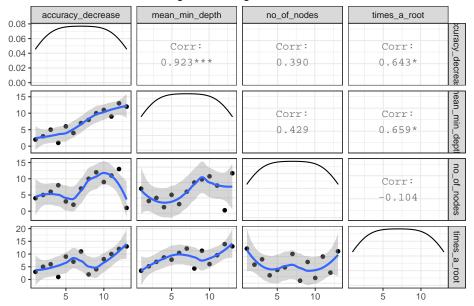
`geom_smooth()` using formula 'y ~ x'

```
#plot_importance_ggpairs(importance_frame)
plot_importance_rankings(importance_frame, measures=c("accuracy_decrease", "mean_min_depth", "no_of_nod

## `geom_smooth()` using formula 'y ~ x'

## `geom_smooth()` using formula 'y ~ x'
```

Relations between rankings according to different measures



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print(important_parameters)

We run the interaction analysis and find the importance of interactions:

kable(full_interactions_frame) %>% kable_styling(latex_options="scale_down")

variable	root_variable	mean_min_depth	occurrences	interaction	uncond_mean_min_depth
ants	q0	0.9932660	297	q0:ants	1.2200000
$\overline{q0}$	q0	0.8989899	297	q0:q0	0.8933333
rho	q0	1.1212121	297	q0:rho	1.6233333
beta	q0	0.8831650	296	q0:beta	1.6133333
dummy	q0	1.7764310	295	q0:dummy	2.6100000
beta	beta	2.3166554	280	beta:beta	1.6133333
beta	rho	2.0961279	280	rho:beta	1.6133333
beta	ants	2.2905724	279	ants:beta	1.6133333
rho	ants	2.3309764	279	ants:rho	1.6233333
ants	beta	2.8853199	276	beta:ants	1.2200000
$\overline{q0}$	rho	2.4550505	276	rho:q0	0.8933333
rho	rho	2.8085859	276	rho:rho	1.6233333
ants	ants	2.8598204	275	ants:ants	1.2200000
rho	beta	2.7522334	275	beta:rho	1.6233333
$\overline{q0}$	ants	2.8363636	273	ants:q0	0.8933333
dummy	ants	3.3700898	272	ants:dummy	2.6100000
$\overline{q0}$	beta	3.1761167	271	beta:q0	0.8933333
ants	rho	3.0405724	270	rho:ants	1.2200000
dummy	beta	3.6625589	270	beta:dummy	2.6100000
dummy	rho	3.4119529	268	rho:dummy	2.6100000
beta	dummy	3.5158249	237	dummy:beta	1.6133333
rho	dummy	4.0573176	230	dummy:rho	1.6233333
dummy	dummy	5.3166891	220	dummy:dummy	2.6100000
q0	dummy	4.7113356	217	dummy:q0	0.8933333
ants	dummy	4.6722896	216	dummy:ants	1.2200000

Once we filter dummy interactions and aggregate bidirectional interactions we get a matrix where the importance of interactions are summarized:

print(interactions_frame)

```
variable\ {\tt root\_variable}\ {\tt mean\_min\_depth}\ {\tt occurrences}\ {\tt interaction}
## 1
          ants
                            q0
                                       0.993266
                                                          570
                                                                   q0:ants
## 2
                            q0
                                                          573
           rho
                                       1.121212
                                                                     q0:rho
## 3
                                       0.883165
                                                          567
                                                                    q0:beta
          beta
                            q0
##
    uncond_mean_min_depth
## 1
                    1.220000
## 2
                    1.623333
## 3
                    1.613333
```