Data-driven Model Falsification in Python

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1 Data-driven Model Falsification Module

For a theoretical overview on model falsification please see:

- 1. De, Subhayan, et al. "Investigation of model falsification using error and likelihood bounds with application to a structural system." *Journal of Engineering Mechanics* 144.9 (2018): 04018078.
- 2. De, Subhayan, et al. "A hybrid probabilistic framework for model validation with application to structural dynamics modeling." *Mechanical Systems and Signal Processing* 121 (2019): 961-980.

Download the module from https://github.com/subhayande/Model_Falsification. See the demo (fals_test1.py) for an example of the implementation.

Required packages: numpy, scipy, time

NOTE: Currently, only Gaussian distributions for residual errors are allowed and two-sided hypothesis tests are implemented.

Report any bugs to Subhayan.De@colorado.edu

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1.1 Procedures implemented

Error-bound and Likelihood-bound model falsification using error criteria:

- Familywise error rate (FWER)
 - Bonferroni
 - Sidák
- False discovery rate (FDR)
 - BH procedure

1.2 EBBonferroni

Error-bound Falsification class using Bonferroni criterion	
	(derived from Error-bound Falsification class)
==========	
Initialization:	
Fals = EBBonfer	roni(nModels, nMeas, alpha, paramDist, distVar, meas, func,
residualSD)	
=======================================	
Attributes:	
models:	Model instances
nModels:	Total number of models
nParam:	Number of uncertain parameter in a model
<pre>paramDist:</pre>	Names of the probability distributions of the uncertain
parameters.	
	orts normal/gaussian, uniform, lognormal)
distVar:	Variables of the uncertain parameter distribution
nMeas:	Total number of measurements
predictions:	Predictions by the models
residualSD:	Standard deviation of the residual error
pValues:	p values for predictions from all the models
alphaValues:	alpha values for predictions from all the models
func:	prediction function
version:	version of the code
Methods:	
doFalsification	: performs falsification
using Bonferroni correction	
inherited:	
genModels:	generates all the model instances
funEval:	predicts
	: calculates alpha and p values
•	
Reference: De, S., Brewick, P.T., Johnson, E.A. and Wojtkiewicz, S.F., 2018 "Investigation of Model Falsification Using Error and Likelihood Bounds with Application to a Structural System." Journal of Engineering Mechanics, 144(9), p.04018078.	
written by Subhayan De (email:Subhayan.De@colorado.edu)	
1.3 EBSidak	
	or-bound Falsification class using Sidak criterion
(derived from Error-bound Falsification class)	

Initialization:

Fals = EBSidak(nModels, nMeas, alpha, paramDist, distVar, meas, func,
residualSD)

Attributes:

models: Model instances

nModels: Total number of models

nParam: Number of uncertain parameter in a model

paramDist: Names of the probability distributions of the uncertain

parameters.

(Currently supports normal/gaussian, uniform, lognormal)

distVar: Variables of the uncertain parameter distribution

nMeas: Total number of measurements predictions: Predictions by the models

residualSD: Standard deviation of the residual error pValues: p values for predictions from all the models alphaValues: alpha values for predictions from all the models

Methods:

doFalsification: performs falsification using Sidak correction

inherited:

genModels: generates all the model instances

funEval: predicts

getAlphapValues: calculates alpha and p values

Reference: De, S., Brewick, P.T., Johnson, E.A. and Wojtkiewicz, S.F., 2018 "Investigation of Model Falsification Using Error and Likelihood Bounds with Application to a Structural System."

Journal of Engineering Mechanics, 144(9), p.04018078.

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1.4 EBBH

| Error-bound Falsification class using BH procedure | (derived from Error-bound Falsification class)

Initialization:

Fals = EBBH(nModels, nMeas, alpha, paramDist, distVar, meas, func,
residualSD)

Attributes:

models: Model instances

nModels: Total number of models

nParam: Number of uncertain parameter in a model

paramDist: Names of the probability distributions of the uncertain

parameters.

(Currently supports normal/gaussian, uniform, lognormal)

distVar: Variables of the uncertain parameter distribution

nMeas: Total number of measurements predictions: Predictions by the models

residualSD: Standard deviation of the residual error pValues: p values for predictions from all the models alphaValues: alpha values for predictions from all the models

Methods:

doFalsification: performs falsification using BH procedure

inherited:

genModels: generates all the model instances

funEval: predicts

getAlphapValues: calculates alpha and p values

Reference: De, S., Brewick, P.T., Johnson, E.A. and Wojtkiewicz, S.F., 2018 "Investigation of Model Falsification Using Error and Likelihood Bounds

with Application to a Structural System."

Journal of Engineering Mechanics, 144(9), p.04018078.

written by Subhayan De (email:Subhayan.De@colorado.edu)

1.5 LBBonferroni

Likelihood-bound Falsification class using Bonferroni criterion (derived from Likelihood-bound Falsification class)

Initialization:

Fals = LBBonferroni(nModels, nMeas, alpha, paramDist, distVar, meas, func,
residualSD)

Attributes:

models: Model instances

nModels: Total number of models

nParam: Number of uncertain parameter in a model

paramDist: Names of the probability distributions of the uncertain

parameters.

(Currently supports normal/gaussian, uniform, lognormal)

distVar: Variables of the uncertain parameter distribution

nMeas: Total number of measurements predictions: Predictions by the models

residualSD: Standard deviation of the residual error pValues: p values for predictions from all the models alphaValues: alpha values for predictions from all the models

Methods:

doFalsification: performs falsification using

Bonferroni criterion

inherited:

genModels: generates all the model instances

funEval: predicts

getAlphapValues: calculates alpha and p values

Reference: De, S., Brewick, P.T., Johnson, E.A. and Wojtkiewicz, S.F., 2018 "Investigation of Model Falsification Using Error and Likelihood Bounds

with Application to a Structural System."

Journal of Engineering Mechanics, 144(9), p.04018078.

written by Subhayan De (email:Subhayan.De@colorado.edu)

1.6 LBSidak

Likelihood-bound Falsification class using Sidak criterion (derived from Likelihood-bound Falsification class)

Initialization:

Fals = LBSidak(nModels, nMeas, alpha, paramDist, distVar, meas, func,
residualSD)

Attributes:

models: Model instances

nModels: Total number of models

nParam: Number of uncertain parameter in a model

paramDist: Names of the probability distributions of the uncertain

parameters.

(Currently supports normal/gaussian, uniform, lognormal)

distVar: Variables of the uncertain parameter distribution

nMeas: Total number of measurements predictions: Predictions by the models

residualSD: Standard deviation of the residual error pValues: p values for predictions from all the models alphaValues: alpha values for predictions from all the models

func: prediction function
version: version of the code

Methods:

doFalsification: performs falsification using

Bonferroni criterion

inherited:

genModels: generates all the model instances

funEval: predicts

getAlphapValues: calculates alpha and p values

Reference: De, S., Brewick, P.T., Johnson, E.A. and Wojtkiewicz, S.F., 2018 "Investigation of Model Falsification Using Error and Likelihood Bounds

with Application to a Structural System."

Journal of Engineering Mechanics, 144(9), p.04018078.

written by Subhayan De (email:Subhayan.De@colorado.edu)

1.7 LBBH

Likelihood-bound Falsification class using BH procedure (derived from Likelihood-bound Falsification class)

Initialization:

Fals = LBBH(nModels, nMeas, alpha, paramDist, distVar, meas, func,
residualSD)

Attributes:

models: Model instances

nModels: Total number of models

nParam: Number of uncertain parameter in a model

paramDist: Names of the probability distributions of the uncertain

parameters.

(Currently supports normal/gaussian, uniform, lognormal)

distVar: Variables of the uncertain parameter distribution

nMeas: Total number of measurements predictions: Predictions by the models

residualSD: Standard deviation of the residual error pValues: p values for predictions from all the models alphaValues: alpha values for predictions from all the models

Methods:

doFalsification: performs falsification using

Bonferroni criterion

inherited:

genModels: generates all the model instances

funEval: predicts

2 Example

NOTE: Implementation of this example is in:

Consider the following linear regression problem:

$$y = 3 + 4.5x + \text{noise} \tag{1}$$

where the regression parameters are $\theta = [3, 4.5]^T$. Using 200 measurements the above methods are implemented. The priors for the coefficients are assumed as $\mathcal{U}(2,5)$ and $\mathcal{N}(4,0.5^2)$, *i.e.*, uniform and Gaussian, respectively. The problem is initialized using

```
# number of measurements
nMeas = 200
# parameters
w1 = 3.0
w2 = 4.5
# noisy data
X = 2.0*np.random.rand(nMeas,1)
np.savetxt('fals1_data.txt',X)
y = w1 + w2 * X + np.random.randn(nMeas,1)
# Model definition
thetaDist = np.array(['uniform', 'normal'])
modelDistVar = np.array([[2,5],[4.0,0.5]])
def fun(param):
    function to calculate model predictions
    X = np.loadtxt('fals1_data.txt')
    pred = param[0] + param[1]*X
    return pred
```

2.1 EBBonferroni

```
from Falsification import EBBonferroni
```

fls.doFalsification() # perform falsification

The output is shown below:

Using Error-bound model falsification with Bonferroni criterion

Total number of candidate models = 1000

STEP I: Generating candidate models

Error-bound Bonferroni | 100.0% Complete:
Time Elapsed = 0.0s

STEP II: Predicting using candidate models

Error-bound Bonferroni | 100.0% Complete:
Time Elapsed = 1.83s

STEP III: Calculating alpha and p values

Error-bound Bonferroni | 100.0% Complete: Time Elapsed = 77.26s

STEP IV: Falsifying models

Error-bound Bonferroni | 100.0% Complete:
Time Elapsed = 77.57s

Number of unfalsified models = 573

Percent unfalsified = 57.30 %

2.2 EBSidak

from Falsification import EBSidak

```
fls = EBSidak(nModels =1000, nMeas=nMeas, alpha=0.05,
             paramDist=thetaDist, distVar=modelDistVar,
             meas = y, func = fun, residualSD = 1.0) # initialize
fls.doFalsification() # perform falsification
The output is the following:
Using Error-bound model falsification with Sidak criterion
Total number of candidate models = 1000
_____
STEP I: Generating candidate models
Error-bound Sidak |
                                                  | 100.0% Complete:
Time Elapsed = 0.0s
______
STEP II: Predicting using candidate models
Error-bound Sidak |
                                                  | 100.0% Complete:
Time Elapsed = 1.82s
STEP III: Calculating alpha and p values
Error-bound Sidak |
                                                  | 100.0% Complete:
Time Elapsed = 76.23s
STEP IV: Falsifying models
Error-bound Sidak |
                                                  | 100.0% Complete:
Time Elapsed = 76.53s
Number of unfalsified models = 572
Percent unfalsified = 57.20 %
2.3 EBBH
```

from Falsification import EBBH

fls = EBBH(nModels =1000, nMeas=nMeas, alpha=0.05,

```
paramDist=thetaDist, distVar=modelDistVar,
          meas = y, func = fun, residualSD = 1.0) # initialize
fls.doFalsification() # perform falsification
The output is the following:
Using Error-bound model falsification with BH procedure
Total number of candidate models = 1000
STEP I: Generating candidate models
Error-bound BH procedure |
                                                           | 100.0% Complete:
Time Elapsed = 0.0s
STEP II: Predicting using candidate models
Error-bound BH procedure |
                                                           | 100.0% Complete:
Time Elapsed = 1.92s
_____
STEP III: Calculating alpha and p values
Error-bound BH procedure
                                                           | 100.0% Complete:
Time Elapsed = 79.53s
STEP IV: Falsifying models
Error-bound BH procedure |
                                                           | 100.0% Complete:
Time Elapsed = 79.86s
Number of unfalsified models = 507
Percent unfalsified = 50.70 %
2.4 LBBonferroni
from Falsification import LBBonferroni
fls = LBBonferroni(nModels =1000, nMeas=nMeas, alpha=0.05,
                  paramDist=thetaDist, distVar=modelDistVar,
```

meas = y, func = fun, residualSD = 0.4) # initialize

```
fls.doFalsification() # perform falsification
The output is the following:
Using Likelihood-bound model falsification with Bonferroni criterion
Total number of models = 1000
._____
STEP I: Generating candidate models
Likelihood-bound Bonferroni criterion
                                | 100.0% Complete:
Time Elapsed = 0.0s
STEP II: Predicting using candidate models
Likelihood-bound Bonferroni criterion
                                | 100.0% Complete:
Time Elapsed = 1.96s
_____
STEP III: Calculating alpha and p values
Likelihood-bound Bonferroni criterion
                                | 100.0% Complete:
Time Elapsed = 79.68s
STEP IV: Calculating likelihood of the candidate models
Likelihood-bound Bonferroni criterion
                                | 100.0% Complete:
Time Elapsed = 111.81s
._____
STEP V: Falsifying models
Likelihood-bound Bonferroni criterion
                                | 100.0% Complete:
Time Elapsed = 112.08s
```

Number of unfalsified models = 595

```
Percent unfalsified = 59.50 %
```

2.5 LBSidak

```
from Falsification import LBSidak
```

fls.doFalsification() # perform falsification

The output is the following:

Using Likelihood-bound model falsification with Sidak criterion

Total number of models = 1000

STEP I: Generating candidate models

Likelihood-bound Sidak criterion | 100.0% Complete:

Time Elapsed = 0.0s

STEP II: Predicting using candidate models

Likelihood-bound Sidak criterion | 100.0% Complete:

Time Elapsed = 1.98s

STEP III: Calculating alpha and p values

Likelihood-bound Sidak criterion |

100.0% Complete:

Time Elapsed = 79.37s

STEP IV: Calculating likelihood of the candidate models

Likelihood-bound Sidak criterion | 100.0% Complete:

Time Elapsed = 111.25s

```
_____
STEP V: Falsifying models
Likelihood-bound Sidak criterion |
100.0% Complete:
Time Elapsed = 111.52s
Number of unfalsified models = 592
Percent unfalsified = 59.20 %
2.6 LBBH
from Falsification import LBBH
fls = LBBH(nModels =1000, nMeas=nMeas, alpha=0.05,
          paramDist=thetaDist, distVar=modelDistVar,
          meas = y, func = fun, residualSD = 0.4) # initialize
fls.doFalsification() # perform falsification
The output is the following:
Using Likelihood-bound model falsification with BH procedure
Total number of models = 1000
STEP I: Generating candidate models
Likelihood-bound BH procedure |
                                                      | 100.0% Complete:
Time Elapsed = 0.0s
_____
STEP II: Predicting using candidate models
Likelihood-bound BH procedure |
                                                     | 100.0% Complete:
Time Elapsed = 1.97s
_____
STEP III: Calculating alpha and p values
Likelihood-bound BH procedure |
                                                     | 100.0% Complete:
```

Time Elapsed = 80.2s

STEP IV: Calculating likelihood of the candidate models

Likelihood-bound BH procedure | 100.0% Complete:

Time Elapsed = 112.59s

STEP V: Falsifying models

Likelihood-bound BH procedure | 100.0% Complete: Time Elapsed = 112.85s

Number of unfalsified models = 185

Percent unfalsified = 18.50 %