SparseRegression.jl

https://github.com/joshday/SparseRegression.jl

- Josh Day (`@joshday`)
- emailjoshday@gmail.com

A brief History of JuliaML

- Created at last year's JuliaCon
- Then a lot of stuff happened:
  - LearnBase, LossFunctions, PenaltyFunctions, LearningStrategies, Transformations, MLDataUtils, Reinforce,...

SparseRegression

Using the JuliaML ecosystem for high-performance algorithms:

- LossFunctions
- PenaltyFunctions
- LearningStrategies

LossFunctions.jl

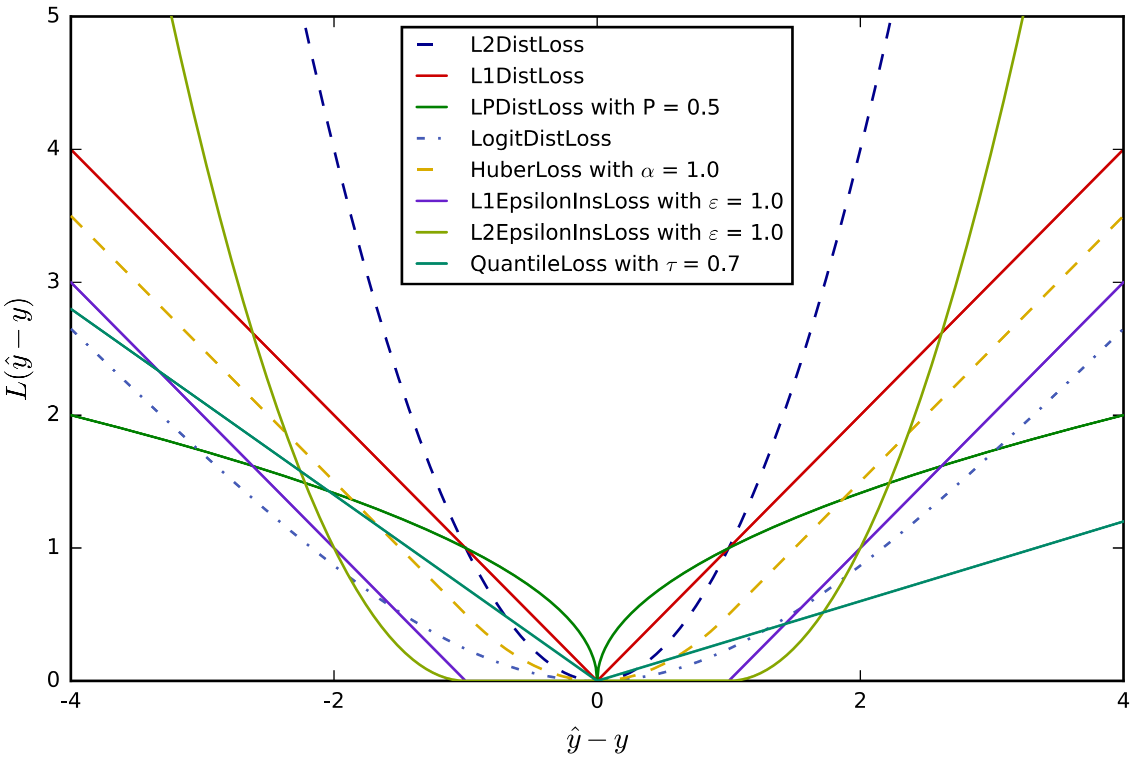
Primary Author: Christof Stocker (evizero)

- Grammar of losses

```
loss = L2DistLoss()
value(loss, 1, 2)
deriv(loss, 1, 2)
```

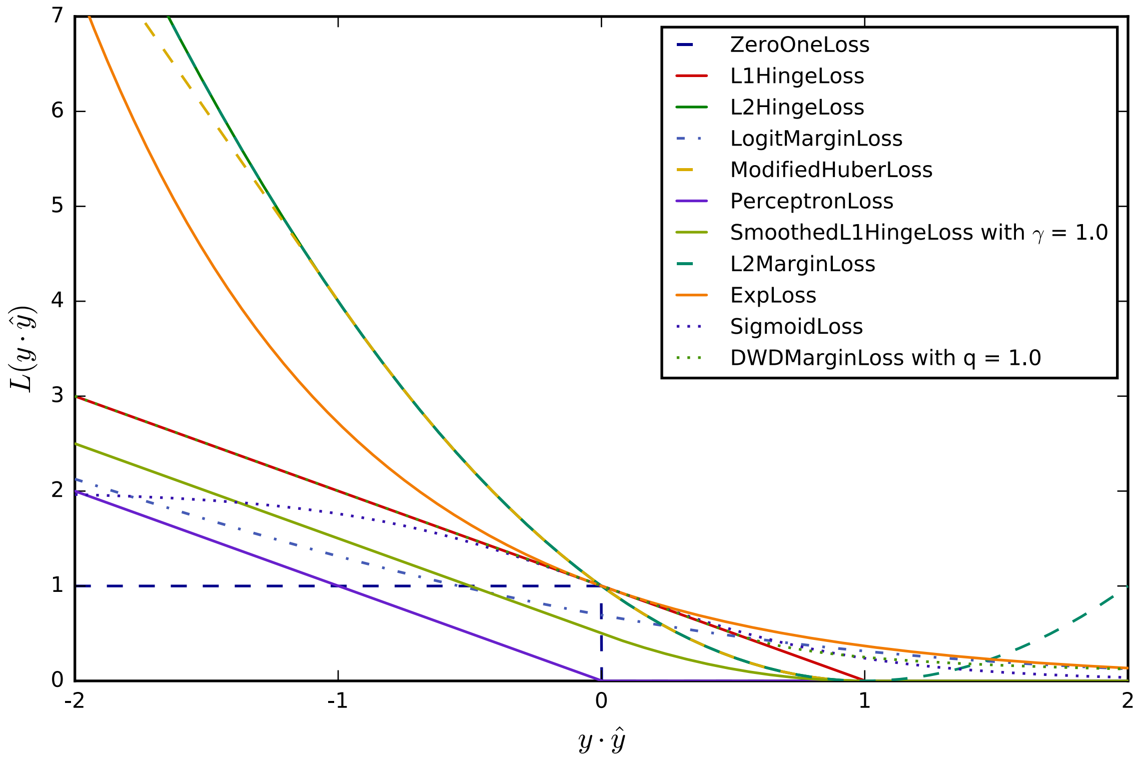
LossFunctions.jl

Distance-based losses $(y - \hat{y})$



LossFunctions.jl

Margin-based losses ($y * \hat{y}$)



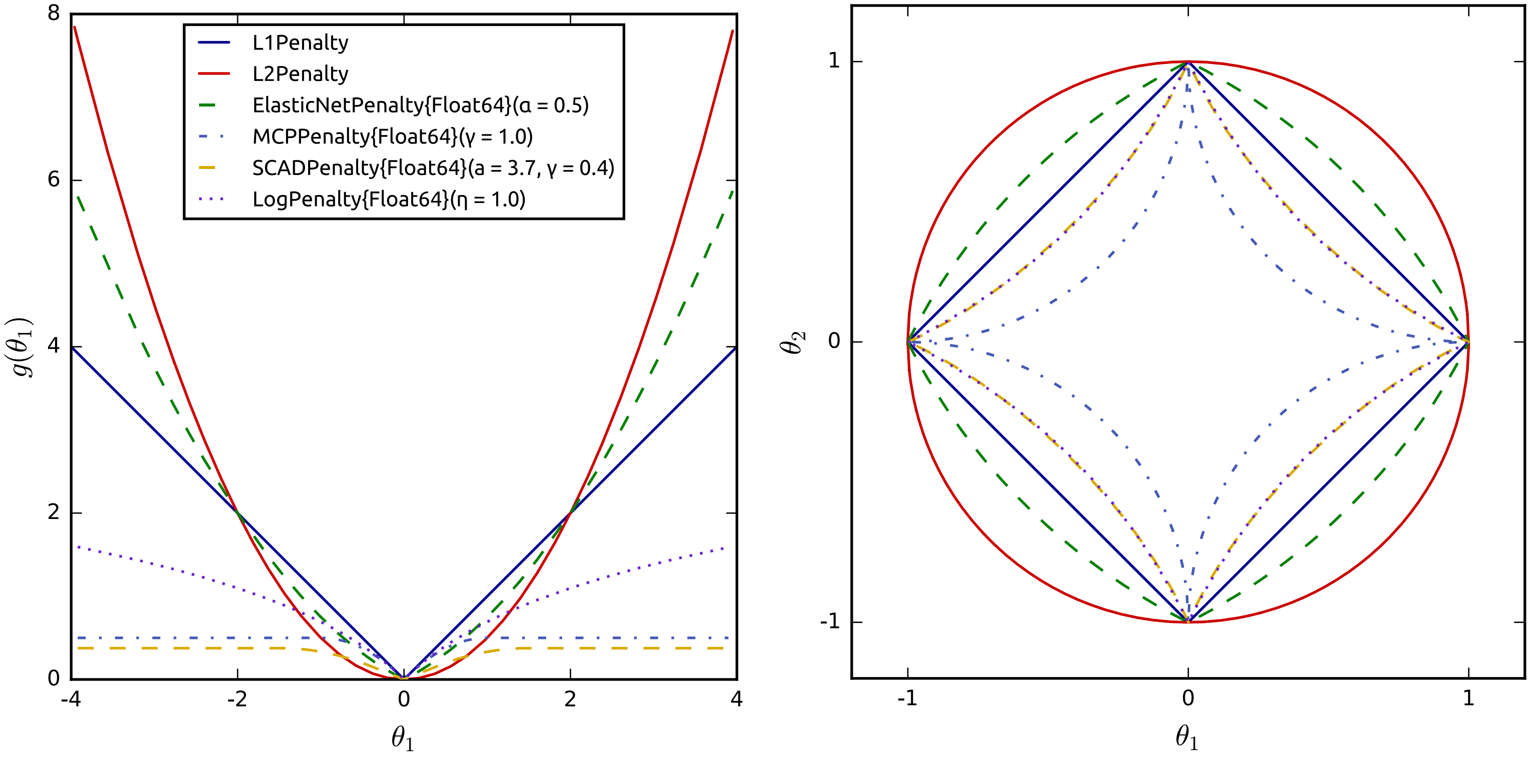
PenaltyFunctions.jl

Primary Author: me (joshday)

- Grammar of regularization functions

```
pen = L1Penalty()
value(pen, .1)
deriv(pen, .1)
```

PenaltyFunctions.jl



LearningStrategies.jl

Primary Author: Tom Breloff (tbreloff)

LearningStrategies.jl

- Separate the components of iterative learning algorithms
    - `MaxIter(n)`
    - `TimeLimit(nsecs)`
    - `Converged(f, tol)`

LearningStrategies

```julia
function learn!(model, meta::MetaLearner, data)
    pre_hook(meta, model)

    for (i, item) in enumerate(data)
        for mgr in meta.managers
            learn!(model, mgr, item)
        end
        iter_hook(meta, model, i)
        finished(meta, model, i) && break
    end

    post_hook(meta, model)
end
```

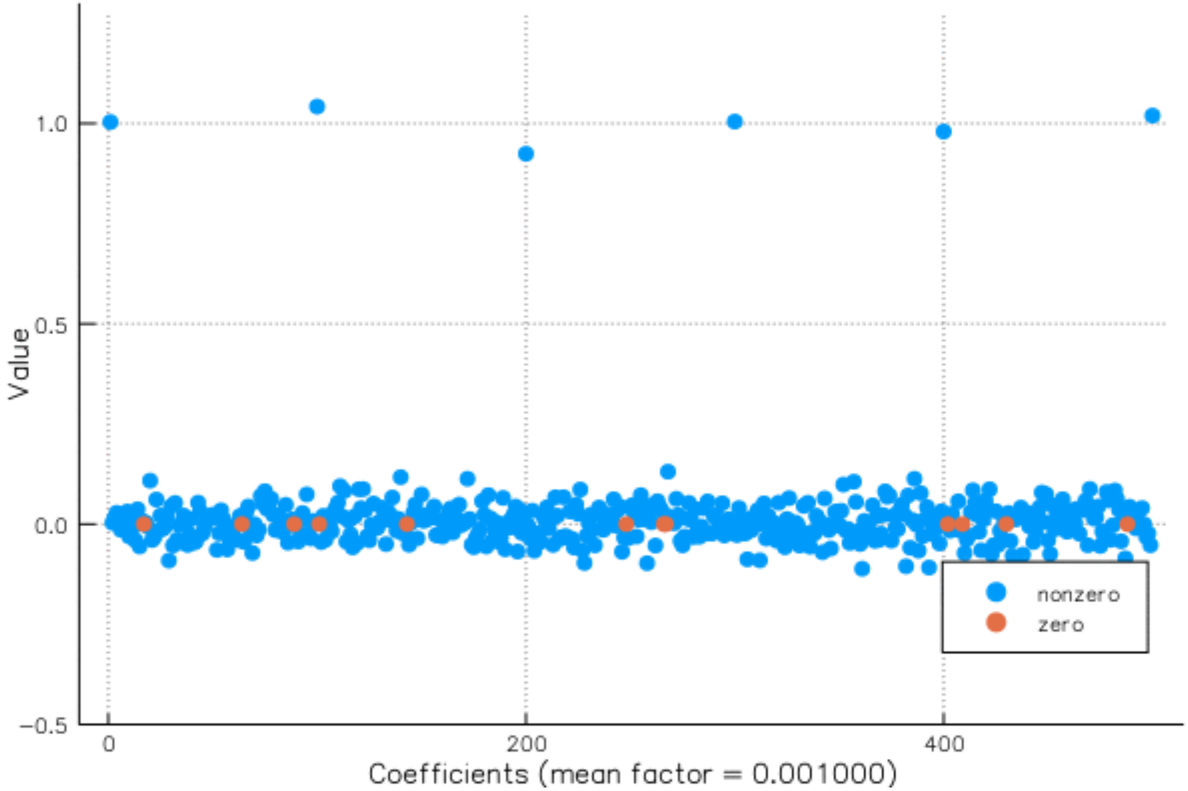
The SparseRegression Model

$$\frac{1}{n}\sum_{i=1}^{n} f_i(\beta) + \sum_{j=1}^{p} \lambda_j J(|\beta_j|)$$

```julia
struct SparseReg{L <: Loss, P <: Penalty, O <: Obs}
    β::Vector{Float64}
    λfactor::Vector{Float64}
    loss::L
    penalty::P
    obs::O
end
```

Why *Sparse* Regression

With certain penalties, as λ_j increases, β_j shrinks to 0



SparseRegression

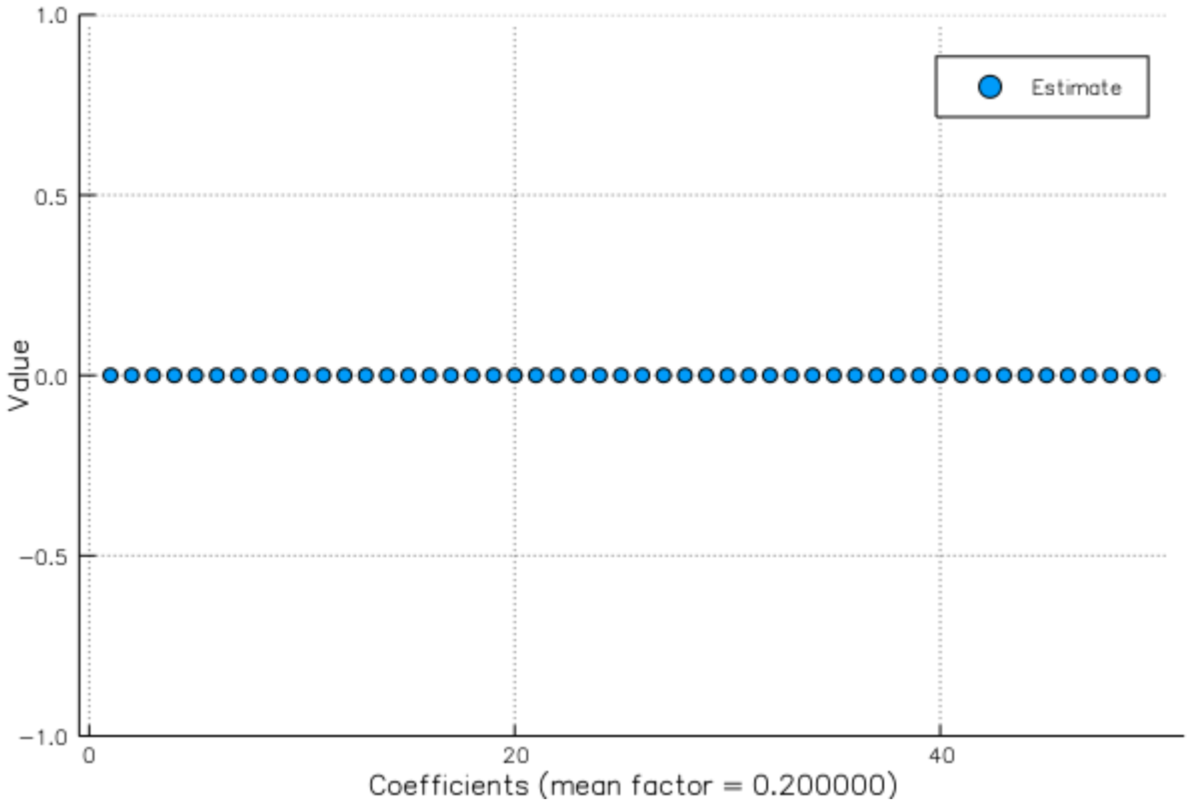
- Brings together primitives from LossFunctions, PenaltyFunctions, and LearningStrategies
- `SparseReg` model type
- Algorithm types, `<: LearningStrategy`

```julia
using SparseRegression, DataGenerator

# First, create some data
x, y, β = linregdata(10_000, 50)
```

```
o = SparseReg(Obs(x, y), LinearRegression(),
    L1Penalty(), fill(.2, 50))
```

```
■ SparseReg
  >           β:  [0.0 0.0 … 0.0 0.0]
  >    λ factor:  [0.2 0.2 … 0.2 0.2]
  >        Loss:  0.5 * (L2DistLoss)
  >     Penalty:  L1Penalty
```

Model Starts "Empty"

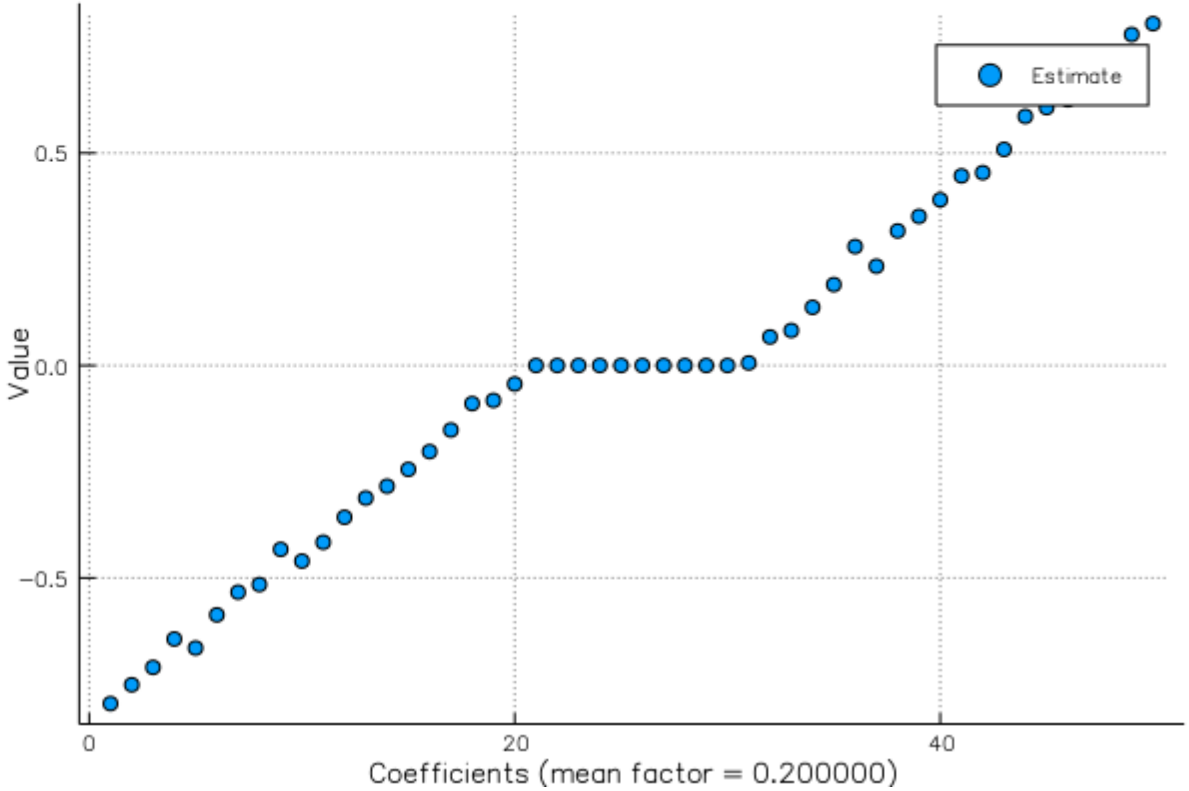


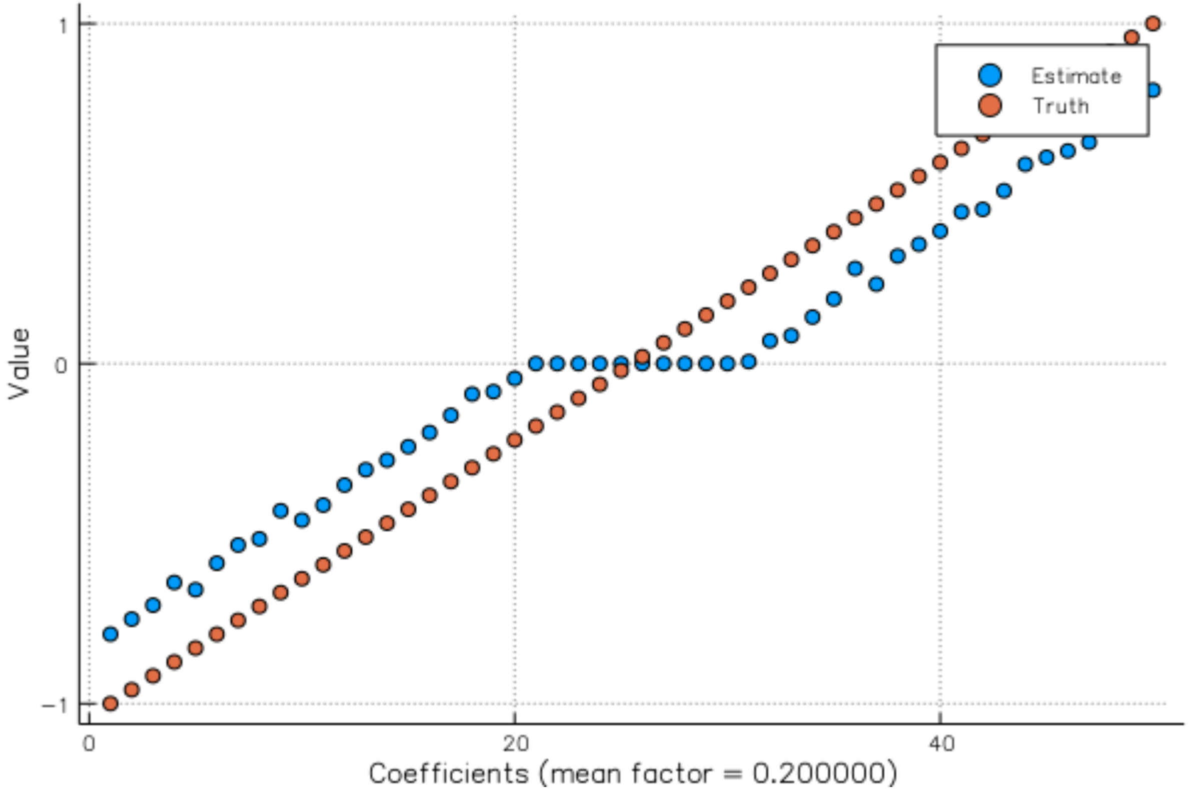
It must be learned!

```
learn!(model, algorithm)
learn!(model, algorithm, maxiter)
learn!(model, algorithm, maxiter, strategies...)
```

```
learn!(o, ProxGrad(), MaxIter(50), Converged(coef))
```

```
INFO: Converged after 8 iterations: [-0.798185, ...
```


Estimate
0.5
0.0
−0.5
Value
0
20
40
Coefficients (mean factor = 0.200000)


1
0
−1
Value
0
20
40
Coefficients (mean factor = 0.200000)
Estimate
Truth

Solution Paths

- Add a parameter α
- Minimize for a variety of α's:

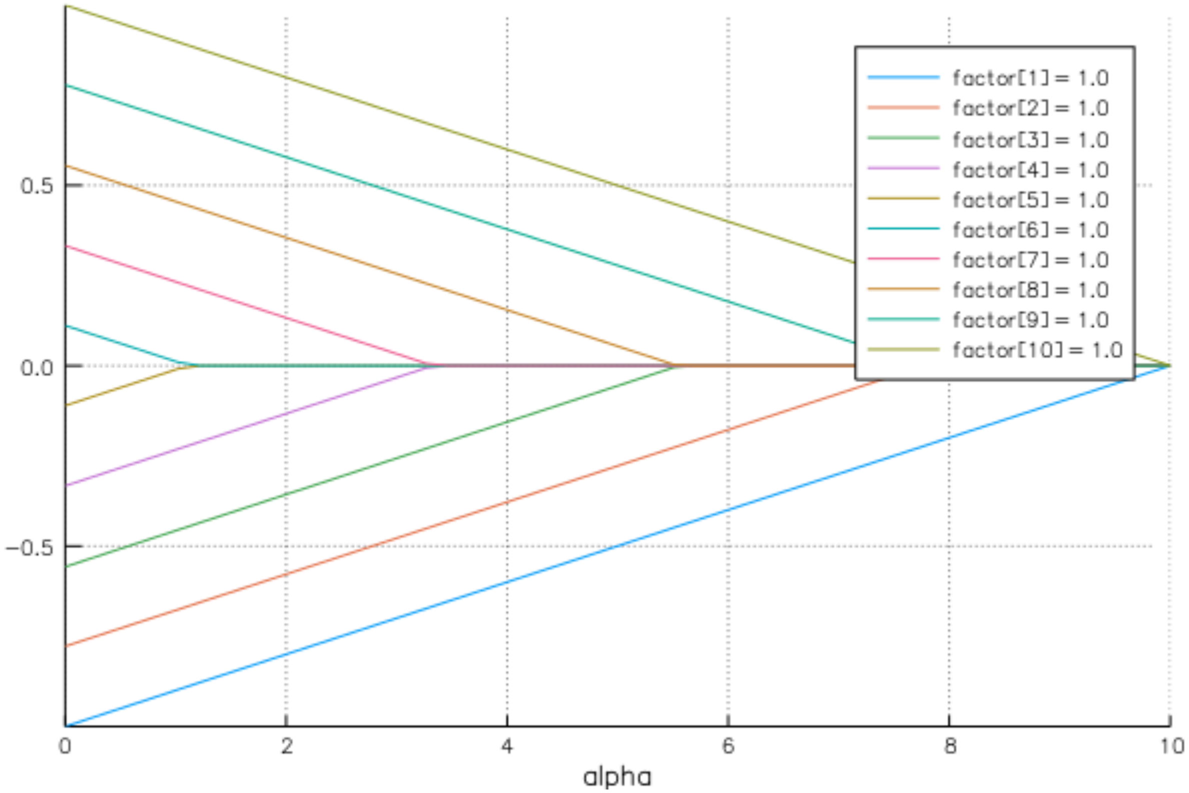
$$\frac{1}{n}\sum_{i=1}^{n} f_i(\beta) + \alpha \sum_{j=1}^{p} \lambda_j J(|\beta_j|)$$

```
x, y, b = linregdata(1_000_000, 10)

o = SparseReg(Obs(x, y), L1Penalty())

path = SparseRegPath(o, linspace(0, 10, 50))

learn!(path, ProxGrad(), MaxIter(20), Converged(coef))
```

```
■ SparseRegPath
  >    λ factor:  [1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0
  >        Loss:  0.5 * (L2DistLoss)
  >     Penalty:  L1Penalty
  > β(0.00) : [-0.999718, -0.776768, -0.555602, ...
  > β(0.20) : [-0.979222, -0.756312, -0.535105, ...
  > β(0.41) : [-0.958725, -0.735857, -0.514608, ...
      ⋮
  > β(9.59) : [-0.0383995, -0.0, -0.0, ...
  > β(9.80) : [-0.0180122, -0.0, -0.0, ...
  > β(10.00) : [-0.0, -0.0, -0.0, ...
```

Plotting

```
plot(path)
```



Note:

We haven't sacrificed performance for generality

```
@btime GLM.lm(x,y);
  2.790 ms (21 allocations: 9.16 MiB)

@btime MultivariateStats.llsq(x, y, bias=false)
  2.395 ms (10 allocations: 1.42 KiB)

@btime learn!(SparseReg(Obs(x,y), NoPenalty()), Sweep())
  2.434 ms (26 allocations: 3.41 KiB)
```

TODOs

- Make work with more AbstractArrays (sparse, other)
- A few opportunities for optimizations
- More algorithms (Coordinate Descent)
- Cross-validation schemes

Final Words

- This is not glmnet
- Easily extendable for new losses, penalties, and algorithms

Thank You