

GENERIC PROGRAMMING IN JULIA

On example of AlternatingProjections.jl: a personal experience

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WHY JULIA?

- Fast to develop
- Fast to execute

A NEW AND *PROMISING* LANGUAGE

- Fast to develop
- Fast to execute
- Just a new shiny thing

A NEW AND PROMISING LANGUAGE

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- Easy to learn

Creating Matrices

MATLAB

PYTHON

JULIA

Create a matrix

```
A = [1 2; 3 4]
```

```
A = np.array([[1, 2], [3, 4]])
```

```
A = [1 2; 3 4]
```

2 x 2 matrix of zeros

```
A = zeros(2, 2)
```

```
A = np.zeros((2, 2))
```

```
A = zeros(2, 2)
```

2 x 2 matrix of ones

```
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```

```
A = np.ones((2, 2))
```

```
A = ones(2, 2)
```

2 x 2 identity matrix

```
A = eye(2, 2)
```

```
A = np.eye(2)
```

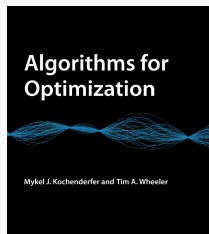
```
A = I # will adopt  
# 2x2 dims if demanded by
```

A NEW AND PROMISING LANGUAGE

- Fast to develop
- Fast to execute
- Just a new shiny thing
- Easy to learn
- They say it is very close to the “whiteboard coding”

Creating Matrices		
MATLAB	PYTHON	JULIA
Create a matrix		
<code>A = [1 2; 3 4]</code>	<code>A = np.array([[1, 2], [3, 4]])</code>	<code>A = [1 2; 3 4]</code>
2 x 2 matrix of zeros		
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2 x 2 identity matrix		
<code>A = eye(2, 2)</code>	<code>A = np.eye(2)</code>	<code>A = I # will adopt # 2x2 dims if demanded by</code>

A talk from JuliaCon I've seen —they've written the whole book which is compiled in Julia



iteration for Adam are:

$$\text{biased decaying momentum: } \mathbf{v}^{(k+1)} = \gamma_v \mathbf{v}^{(k)} + (1 - \gamma_v) \mathbf{g}^{(k)} \quad (5.29)$$

$$\text{biased decaying sq. gradient: } \mathbf{s}^{(k+1)} = \gamma_s \mathbf{s}^{(k)} + (1 - \gamma_s) (\mathbf{g}^{(k)} \odot \mathbf{g}^{(k)}) \quad (5.30)$$

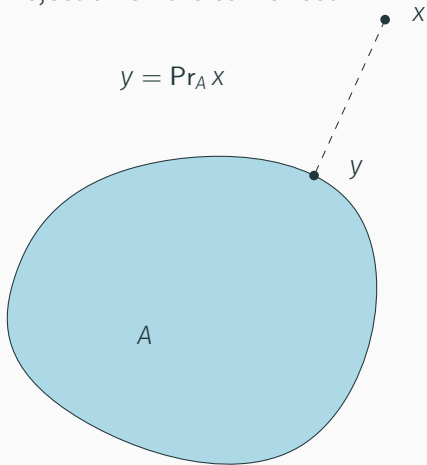
$$\text{corrected decaying momentum: } \hat{\mathbf{v}}^{(k+1)} = \mathbf{v}^{(k+1)} / (1 - \gamma_v^k) \quad (5.31)$$

$$\text{corrected decaying sq. gradient: } \hat{\mathbf{s}}^{(k+1)} = \mathbf{s}^{(k+1)} / (1 - \gamma_s^k) \quad (5.32)$$

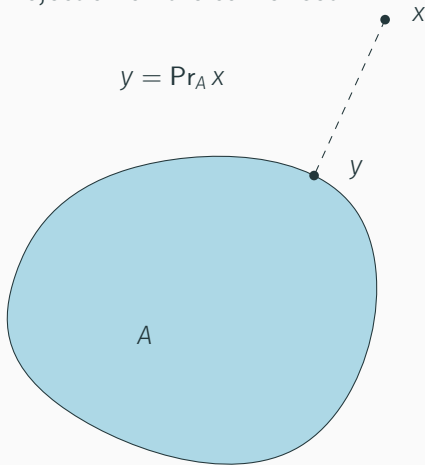
$$\text{next iterate: } \mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} - \alpha \hat{\mathbf{v}}^{(k+1)} / \left(\epsilon + \sqrt{\hat{\mathbf{s}}^{(k+1)}} \right) \quad (5.33)$$

```
mutable struct Adam <: DescentMethod
    α # learning rate
    γv # decay
    γs # decay
    ε # small value
    k # step counter
    v # 1st moment estimate
    s # 2nd moment estimate
end
function init!(M::Adam, f, ∇f, x)
    M.k = 0
    M.v = zeros(length(x))
    M.s = zeros(length(x))
    return M
end
function step!(M::Adam, f, ∇f, x)
    α, γv, γs, ε, k = M.α, M.γv, M.γs, M.ε, M.k
    s, v, g = M.s, M.v, ∇f(x)
    v[:] = γv*v + (1-γv)*g
    s[:] = γs*s + (1-γs)*g.*g
    M.k = k + 1
    v_hat = v ./ (1 - γv^k)
    s_hat = s ./ (1 - γs^k)
    return x - α*v_hat ./ (sqrt.(s_hat) .+ ε)
end
```

Projection on the convex set

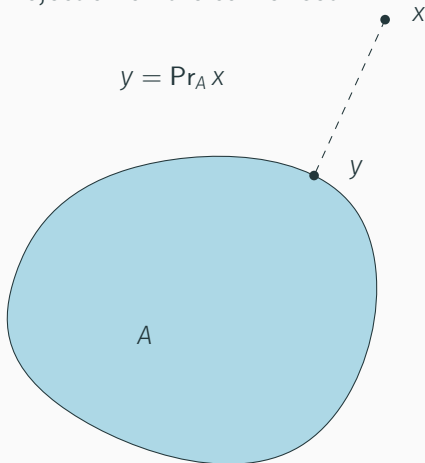


Projection on the convex set



How should I code this?

Projection on the convex set

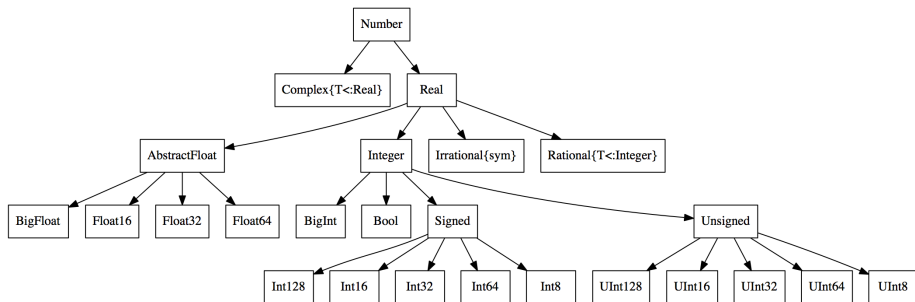


How should I code this?

Is it possible to code abstract concepts?

JULIA'S ABSTRACT AND CONCRETE TYPES

ABSTRACT TYPES FOR CONCEPTS, CONCRETE FOR DATA

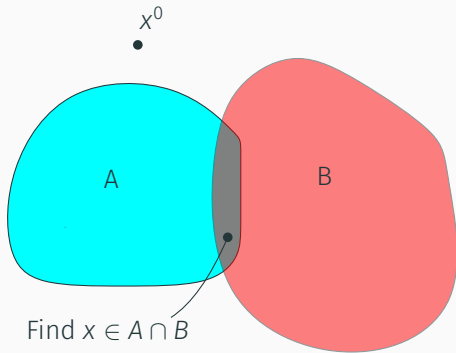


Number types tree

Abstract, concrete and primitive types

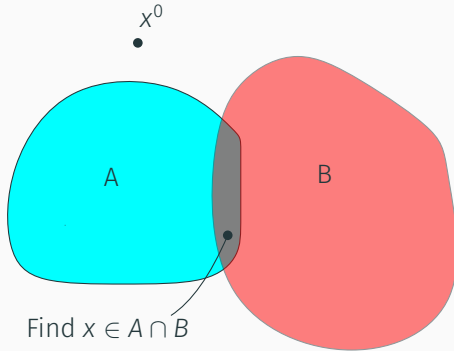
ALTERNATING PROJECTIONS AND ITS RELATIVES

FEASIBILITY PROBLEM



- 1) just any would do
- 2) closest to x^0

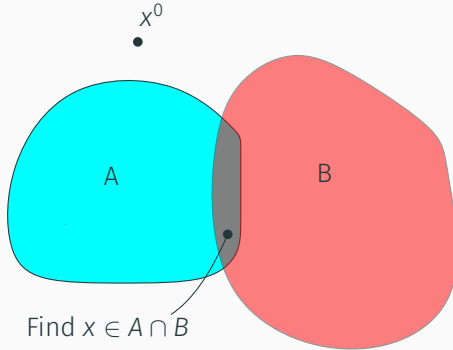
FEASIBILITY PROBLEM



E.g. 1) linear system

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FEASIBILITY PROBLEM



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E.g. 1) linear system

2) phase retrieval problem

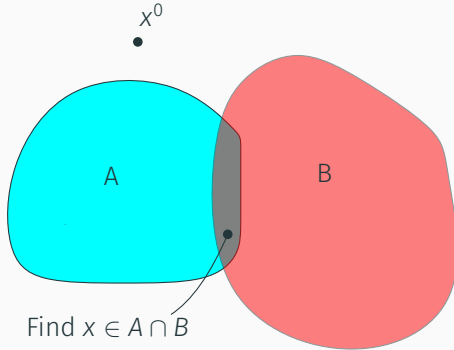
(PR):

$$A = \{x \in \mathbb{C}^{M \times M} : |x| = p\}$$

$$B = \{x \in \mathbb{C}^{M \times M} : |\mathcal{F}x| = P\}$$

p, P are the intensities in pupil and focal planes

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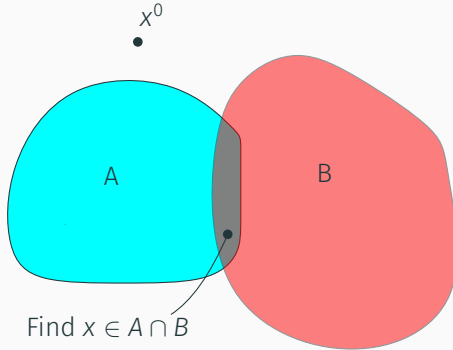
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· Von Neumann: A, B — **convex** \implies use alternating projections (AP)

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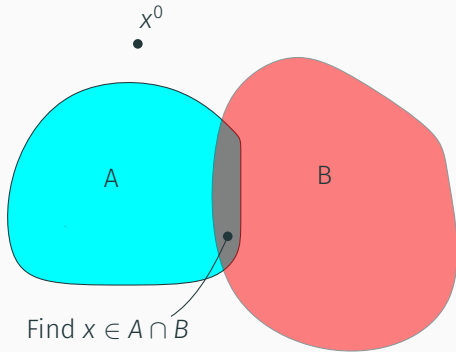
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- H. Thao Ngueng *et al*: A, B should be **(sub)transversal**

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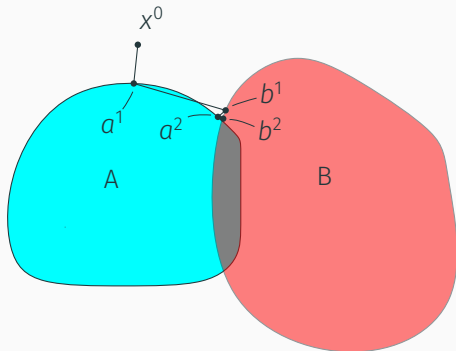
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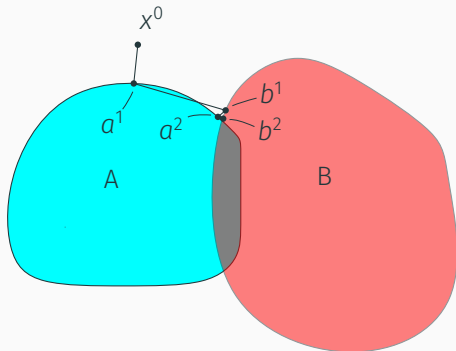
- Von Neumann: A, B — **convex** \implies use alternating projections (AP)
- H. Thao Ngueng *et al*: A, B should be **(sub)transversal**
- The sets in PR problem **are** transversal

ALTERNATING PROJECTIONS FOR THE FEASIBILITY PROBLEM



$$a^1 = \text{Pr}_A x^0$$

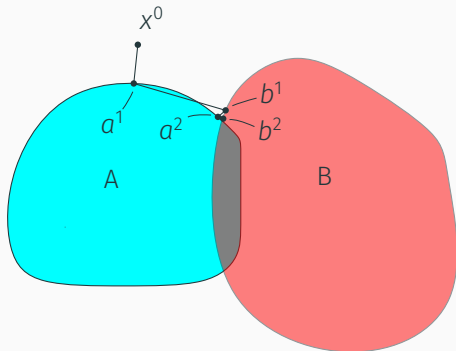
ALTERNATING PROJECTIONS FOR THE FEASIBILITY PROBLEM



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ALTERNATING PROJECTIONS FOR THE FEASIBILITY PROBLEM

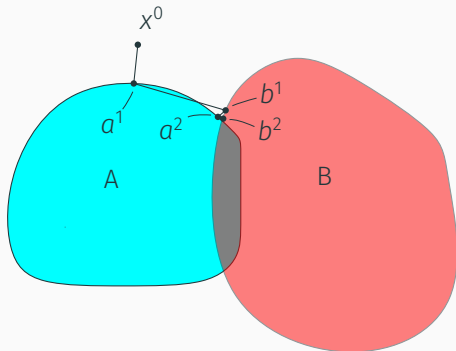


$$a^1 = \text{Pr}_A x^0$$

$$b^1 = \text{Pr}_B a^1$$

$$a^2 = \text{Pr}_A b^1$$

ALTERNATING PROJECTIONS FOR THE FEASIBILITY PROBLEM



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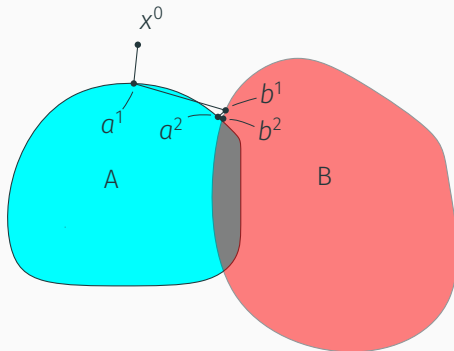
$$b^1 = \text{Pr}_B a^1$$

$$a^2 = \text{Pr}_A b^1$$

...

$$b^k = \text{Pr}_B a^k, a^{k+1} = \text{Pr}_A b^k$$

ALTERNATING PROJECTIONS FOR THE FEASIBILITY PROBLEM



$$a^1 = \text{Pr}_A x^0$$

$$b^1 = \text{Pr}_B a^1$$

$$a^2 = \text{Pr}_A b^1$$

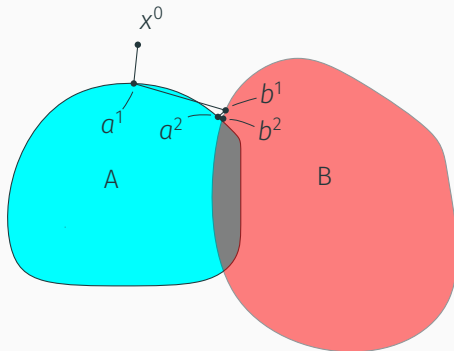
...

$$b^k = \text{Pr}_B a^k, a^{k+1} = \text{Pr}_A b^k$$

Extension with forward and backward operators and *not-so-convex* sets:

$$\text{GS: } X^k = \text{Pr}_P \mathcal{F} X^k, x^{k+1} = \text{Pr}_p \mathcal{F}^{-1} X^k$$

ALTERNATING PROJECTIONS FOR THE FEASIBILITY PROBLEM



$$a^1 = \text{Pr}_A x^0$$

$$b^1 = \text{Pr}_B a^1$$

$$a^2 = \text{Pr}_A b^1$$

...

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Extension with forward and backward operators and *not-so-convex* sets:

$$\text{GS: } X^k = \text{Pr}_P \mathcal{F} X^k, X^{k+1} = \text{Pr}_P \mathcal{F}^{-1} X^k$$

$$\text{TIP: } h^k = \text{Pr}_{\mathcal{H}} i /_* o^k, o^{k+1} = \text{Pr}_{\mathcal{O}} i /_* h^k$$

FEASIBLESET, PROBLEM, AND AL- GORITHM

Concepts as independent from each other as possible:

Three main **abstract types**
with subtypes

1. **Set** :> Convex Set :>
Linear subspace
2. **Problem** :> Feasibility
problem
3. **Algorithm** :> AP

Their **concrete types**
(implementations)

1. $ax = b$
2. PR Problem for given p, P
3. AP with parameters (?)

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1. $ax = b$
2. PR Problem for given p, P
3. AP with parameters (?)

```
abstract type FeasibleSet end

abstract type ConvexSet <: FeasibleSet end

abstract type Problem end

struct FeasibilityProblem <: Problem
    A::FeasibleSet
    B::FeasibleSet
    forward
    backward
end

abstract type APMethod end

struct AP <: APMethod
    maxit
    maxε
end
```

THE FIRST PROGRAM

We are ready to program it! For any problem, any initial guess, any algorithm:

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```
function solve(p::Problem,x0,alg::APMethod)
    error("Don't know how to solve ", typeof(p), " with method ",
        ↪  typeof(alg))
end
```

AP METHOD REALISED IN JULIA (FOR ANY PROBLEM)

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end
```

```
function project(x, feasset::FeasibleSet)
    error("Don't know how to project on ", typeof(feasset))
end
```


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We are ready to program it! For any problem, any initial guess, any algorithm:

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```
function project(x, feasset::FeasibleSet)
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end
```

If x allows subtraction, we can immediately write reflection operation for all cases (to be used in DR and DRAP):

```
reflect(x, feasset::FeasibleSet) = 2 * project(x, feasset) - x
```

```

function solve(p::FeasibilityProblem, x0, alg::AP)
    A = p.A
    B = p.B
    forward = p.forward
    backward = p.backward
    maxit = alg.maxit
    maxε = alg.maxε

    k = 0
    xk = x0
    ε = Inf

    while k < maxit && ε > maxε
         $\tilde{y}^k$  = forward(xk)
        yk = project( $\tilde{y}^k$ , B)
         $\tilde{x}^{k+1}$  = backward(yk)
        xk+1 = project( $\tilde{x}^{k+1}$ , A)
        ε = LinearAlgebra.norm(xk+1 - xk)
        #          println(ε)
        k += 1
    end

    println("To converge with $ε accuracy, it took me $k iterations")
    return xk
end

```

GROWING FLESH ON BONES

A convex and not convex examples of often used feasible sets

```
export APMMethod, FeasibleSet, project, ConvexSet, FeasibilityProblem, AP

# Constraints
include("SupportConstraint.jl")
include("AmplitudeConstraint.jl")

# algorithms
include("GerchbergSaxton.jl")
```

```
abstract type SupportConstrained <: ConvexSet end

struct ConstrainedBySupport <: SupportConstrained
    support::Array{Bool}
end
export ConstrainedBySupport

function project(x, feasset::ConstrainedBySupport)
    return feasset.support .* x
end
```

```
julia> using AlternatingProjections

julia> S = ConstrainedBySupport([true, false,true])
ConstrainedBySupport{Bool{1}, 0, 1}

julia> x = [1, 2, 3]
3-element Array{Int64,1}:
 1
 2
 3

julia> project(x, S) == [1, 0, 3]
true
```

```
julia> using AlternatingProjections

julia> S = ConstrainedBySupport([true, false,true])
ConstrainedBySupport{Bool{1}, 0, 1}

julia> x = [1, 2, 3]
3-element Array{Int64,1}:
 1
 2
 3

julia> project(x, S) == [1, 0, 3]
true
```

```
julia> S2 = ConstrainedBySupport([1, 0, 1])
ConstrainedBySupport{Bool{1}, 0, 1}
```

Projection doesn't depend on the support dimension

```
julia> S3=ConstrainedBySupport([0 0 1 0 0; 0 0 1 0 0; 1 1 1 1 1; 0 0 1 0  
↪ 0; 0 0 1 0 0]);
```

```
julia> x = rand{Int8, 5,5}
```

```
5×5 Array{Int8,2}:  
30  -92   16  127   5  
108 100  126 -111  86  
37  -38  -26  -53  -3  
27  114 -103   29  29  
85   -7  -86  -68 -49
```

```
julia> project(x,S3)
```

```
5×5 Array{Int8,2}:  
0   0   16   0   0  
0   0  126   0   0  
37  -38  -26  -53  -3  
0   0 -103   0   0  
0   0  -86   0   0
```



```
julia> P = ConstrainedBySupport([1, 0, 1, 0, 1])
ConstrainedBySupport{Bool{1}, 0, 1, 0, 1}

julia> Q = ConstrainedBySupport([1, 1, 1, 0, 0])
ConstrainedBySupport{Bool{1}, 1, 1, 0, 0}

julia> prb = FeasibilityProblem(P, Q, identity, identity)
FeasibilityProblem{ConstrainedBySupport{Bool{1}, 0, 1, 0, 1},
↳ ConstrainedBySupport{Bool{1}, 1, 1, 0, 0}}, identity, identity)

julia> mth = AP(200, 0.001)
AP{200, 0.001}

julia> sol = solve(prb, [1, 1, 1, 1, 1], mth)
To converge with 0.0 accuracy, it took me 2 iterations
5-element Array{Int64,1}:
 1
 0
 1
 0
 0
```

Just in the same way as explaining in a mathematical prove, we should be able to extend AP to Gerchberg-Saxton method for phase retrieval.

Just introduce the correct sets and explain how to project on them:

$$A = \{x \in \mathbb{C}^{M \times M} : |x| = p\}$$

$$\text{Pr}_A = p \cdot \frac{x}{|x|}$$

```
abstract type AmplitudeConstrainedSet <: FeasibleSet end
export AmplitudeConstrainedSet

struct ConstrainedByAmplitude <: AmplitudeConstrainedSet
    amp::Array{T} where T <: Real #todo nonnegative
end
export ConstrainedByAmplitude

function project(x, feasset::ConstrainedByAmplitude)
    return feasset.amp .* exp.(im * angle.(x))
end
```

```
julia> A = ConstrainedByAmplitude([1, sqrt(2), 5])  
ConstrainedByAmplitude([1.0, 1.4142135623730951, 5.0])
```

```
julia> y = [2im, -2 + 2im, 6 - 8im]  
3-element Array{Complex{Int64},1}:  
0 + 2im  
-2 + 2im  
6 - 8im
```

```
julia> project(y, A) ≈ [im, -1 + im, 3 - 4im]  
true
```

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6 - 8im
```

```
julia> project(y, A) ≈ [im, -1 + im, 3 - 4im]  
true
```

```
julia> project(y, A)  
3-element Array{Complex{Float64},1}:  
6.123233995736766e-17 + 1.0im  
-1.0 + 1.0000000000000002im  
3.0000000000000004 - 3.9999999999999996im
```

```
julia> y = zeros(ComplexF32,10,10);
julia> y[1:5,1:5] = randn(ComplexF32, 5,5);

julia> using FFTW
julia> Y = fft(y)

julia> pr = FeasibilityProblem(ConstrainedByAmplitude(abs.(y)),
↪ ConstrainedByAmplitude(abs.(Y)),fft, ifft);
julia> gs=AP(3000,1e-18);

julia> z= solve(pr, ones(size(y)), gs)
To converge with 3.6638411145107034e-16 accuracy, it took me 3000
↪ iterations
...

julia> abs.(fft(z)) ≈ abs.(Y)
true

julia> abs.(z) ≈ abs.(y)
true
```

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```

Check it on a more serious example, dude!

METHODOLOGY

Further extensions are possible in a similar way: add new types and extend methods on them

TIP: `PositiveSupport <: ConvexSet` and `function deconvolve(i,x)`

DR change `solve(pr,x0, method::DR)` to use reflection-based operators

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DR change `solve(pr,x0, method::DR)` to use reflection-based operators

vector GS: new type of set or change `solve(pr,x0, method::vectorAP)` OR new type of problem?

DIFFERENT WAYS OF ORTHOGONALISATION: FIRST ATTEMPTS

```
struct GS <: APMMethod #todo should be sets part of this or added to the  
↳ step! only?  
    a::AmplitudeConstraint  
    A::AmplitudeConstraint  
end  
  
GS(a::Array, A::Array) = GS(AmplitudeConstraint(a),  
↳ AmplitudeConstraint(A))  
  
function init!(alg::GS, x0)  
    a = alg.a  
    A = alg.A  
    if !( size(a) == size(A) == size(x0) )  
        println("cannot initialise Gerchberg-Saxton, dimensions do  
↳ not match")  
        # raise error or pad a smaller array with zeroes  
        # also can include realingment of the sets to remove any  
        ↳ linear pahse term. But then need to make GS mutable  
        return  
    end  
end  
  
function step!(alg::GS, xk)  
    a = alg.a  
    A = alg.A  
    return project(a, ifft(project(A, fft(xk))))  
end
```

DIFFERENT WAYS OF ORTHOGONALISATION: OOP TRAP

```
function apstep(xk, A::FeasibleSet, B::FeasibleSet, forward, backward)
     $\tilde{y}^k$  = forward(xk)
    yk = project( $\tilde{y}^k$ , B)
     $\tilde{x}^{k+1}$  = backward(yk)
    xk+1 = project( $\tilde{x}^{k+1}$ , A)
end

function apsolve(A, B, ::Type{T}; x0=zeros(size(A)), maxit = 20, maxε
↳ =0.01) where {T<:APMethod}
    alg = T(A,B)
    xprev = x0
    x = xprev
    i = 0
    ε = Inf

    while i < maxit && ε > maxε
        x = apstep(xprev, alg.a, alg.A, alg.forward, alg.backward)
        ε = LinearAlgebra.norm(x - xprev)
        xprev = x
        i += 1
    end

    println("To converge with $ε accuracy, it took me $i iterations")
    return x
end
```

Multiple dispatch: data defines the behaviour of the function (all variables of the function)

OOP: object has a collection of methods (functions), that is only one variable (object type) defines the behaviour of the function

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vs

types and methods

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vs

`solve(::XX,.,::GS)` and `solve(::XX,.,::TIP)`

The second approach is more flexible (can add new things without worrying about the existing ones) and generalisation of auto-method selection `solve(pr,x0)` is easy

CONCLUSIONS

- Writing in Julia promotes “Generic programming” paradigm
- It is indeed similar to mathematical description
- Abstract types represent mathematical concepts and concrete types their implementations
- The orthogonalisation of the types and methods is an iterative process which might bring better understanding and opens possibilities for experimenting with novel methods

<https://github.com/olejorik/AlternatingProjections.jl>

Instructions on how to get started and on the workflow included

<https://olejorik.github.io/AlternatingProjections.jl/docs/build/index.html#Workflow-and-package-structure-1>

References:

- <https://julialang.org/>
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