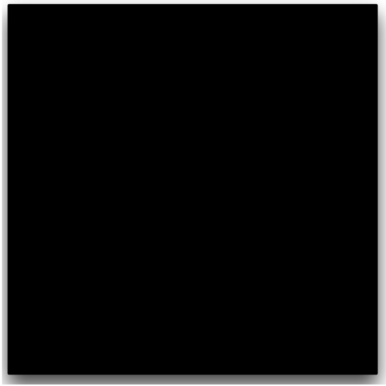
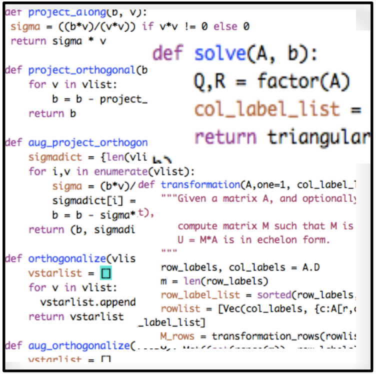
Continuing to look inside the black box



We studied Gaussian elimination, which is used in modules `solver` and `independence` when working over $GF(2)$.

We next study the methods used in these modules when working over $\mathbb{R}$.

Continuing to look inside the black box



We studied Gaussian elimination, which is used in modules `solver` and `independence` when working over $GF(2)$.

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Fire Engine problem

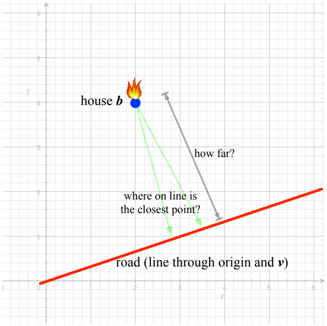
There is a burning house located at coordinates $[2, 4]$!

A street runs near the house, along the line through the origin and through $[6, 2]$—but it is near enough?

Fire engine has a hose 3.5 units long.

If we can navigate the fire engine to the point on the line nearest the house, will the distance be small enough to save the house?

We're faced with two questions: what point along the line is closest to the house, and how far is it?



What do we mean by *closest*?

Distance, length, norm, inner product

We will define the distance between two vectors $\mathbf{p}$ and $\mathbf{b}$ to be the length of the difference $\mathbf{p} - \mathbf{b}$.

This means that we must define the length of a vector.

Instead of using the term "length" for vectors, we typically use the term *norm*.

The norm of a vector $\mathbf{v}$ is written $\|\mathbf{v}\|$

Since it plays the role of length, it should satisfy the following *norm properties*:

Property N1 $\|\mathbf{v}\|$ is a nonnegative real number.

Property N2 $\|\mathbf{v}\|$ is zero if and only if $\mathbf{v}$ is a zero vector.

Property N3 for any scalar α, $\|\alpha\,\mathbf{v}\| = |\alpha|\|\mathbf{v}\|$.

Property N4 $\|\mathbf{u} + \mathbf{v}\| \leq \|\mathbf{u}\| + \|\mathbf{v}\|$ (triangle inequality).

One way to define vector norm is to define an operation on vectors called *inner product*.
Inner product of vectors $\mathbf{u}$ and $\mathbf{v}$ is written

$$\langle \mathbf{u}, \mathbf{v} \rangle$$

The inner product must satisfy certain axioms, which we outline later.

No way to define inner product for $GF(2)$ so no more $GF(2)$ ☹

From inner product to norm

For the real numbers and complex numbers, we have some flexibility in defining the inner product.

This flexibility is used heavily, e.g. in Machine Learning

Once we have defined an inner product, the norm of a vector **u** is defined by

$$\|\mathbf{v}\| = \sqrt{\langle \mathbf{v}, \mathbf{v} \rangle}$$

For simplicity, we will focus on $\mathbb{R}$ and will use the most natural and convenient definition of inner product.

This definition leads to the norm of a vector being the geometric length of its arrow.

For vectors over $\mathbb{R}$, we define our inner product as the dot-product:

$$\langle \mathbf{u}, \mathbf{v} \rangle = \mathbf{u} \cdot \mathbf{v}$$

Properties of inner product of vectors over $\mathbb{R}$

- *linearity in the first argument:* $\langle \mathbf{u} + \mathbf{v}, \mathbf{w} \rangle = \langle \mathbf{u}, \mathbf{w} \rangle + \langle \mathbf{v}, \mathbf{w} \rangle$
- *symmetry:* $\langle \mathbf{u}, \mathbf{v} \rangle = \langle \mathbf{v}, \mathbf{u} \rangle$
- *homogeneity:* $\langle \alpha \mathbf{u}, \mathbf{v} \rangle = \alpha \langle \mathbf{u}, \mathbf{v} \rangle$

For inner product = dot-product, can easily prove these properties.

From inner product to norm

We have defined $\langle \mathbf{u}, \mathbf{v} \rangle = \mathbf{u} \cdot \mathbf{v}$ and $\|\mathbf{v}\| = \sqrt{\langle \mathbf{v}, \mathbf{v} \rangle}$

Do these definitions lead to a norm that satisfies the *norm properties?*

Property N1: $||\mathbf{v}||$ is a nonnegative real number.

Property N2: $||\mathbf{v}||$ is zero if and only if $\mathbf{v}$ is a zero vector.

Property N3: for any scalar α, $||\alpha\, \mathbf{v}|| = |\alpha| ||\mathbf{v}||$.

Property N4: $\|\mathbf{u} + \mathbf{v}\| \leq \|\mathbf{u}\| + \|\mathbf{v}\|$ (triangle inequality).

Write $\mathbf{v} = [v_1, v_2, \ldots, v_n]$.

$\|[v_1, v_2, \ldots, v_n]\| = \sqrt{v_1^2 + v_2^2 + \cdots + v_n^2}$

1. Sum of squares is a nonnegative real number so $\|\mathbf{v}\|$ is nonnegative real number.
2. If any entry v_i of $\mathbf{v}$ is nonzero then sum of squares is nonzero, so norm is nonzero.
3. Proof of third property:

$$
\begin{aligned}
||\alpha\, \mathbf{v}||^2 &= \langle \alpha\, \mathbf{v}, \alpha\, \mathbf{v} \rangle && \text{by definition of norm} \\
&= \alpha\, \langle \mathbf{v}, \alpha\, \mathbf{v} \rangle && \text{by homogeneity of inner product} \\
&= \alpha\, (\alpha\, \langle \mathbf{v}, \mathbf{v} \rangle) && \text{by symmetry and homogeneity (again) of inner product} \\
&= \alpha^2 ||\mathbf{v}||^2 && \text{by definition of norm}
\end{aligned}
$$

Thus $||\alpha\, \mathbf{v}|| = \alpha\, ||\mathbf{v}||$.

We skip the proof of fourth property.

Norm is geometric length of arrow

Example: What is the length of the vector $\mathbf{u} = [u_1, u_2]$?

Remember the *Pythagorean Theorem*:

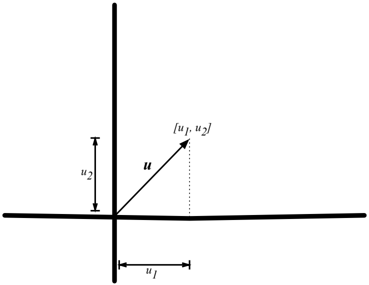
for a right triangle with side-lengths a, b, c*,*
where c *is the length of the hypotenuse,*

$$a^2 + b^2 = c^2$$

We can use this equation to calculate the length of $\mathbf{u}$:

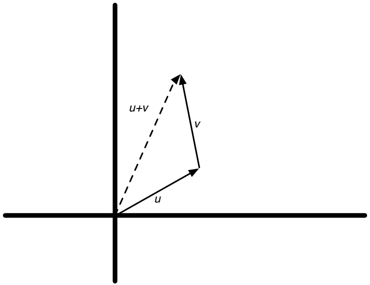
$$(\text{length of } \mathbf{u})^2 = u_1^2 + u_2^2$$

So this notion of length agrees with the one we learned in grade school, at least for vectors in $\mathbb{R}^2$.



Orthogonality

Orthogonal is linear-algebra-ese for *perpendicular*.
We'll define it so as to make Pythagorean Theorem true.
Let $\mathbf{u}$ and $\mathbf{v}$ be vectors.
Their lengths are $||\mathbf{u}||$ and $||\mathbf{v}||$.
Draw the corresponding arrows, and the arrow for $\mathbf{u}+\mathbf{v}$
The arrow for $\mathbf{u}+\mathbf{v}$ is the "hypotenuse". (The triangle is not necessarily a right angle.)



The squared length of the vector $\mathbf{u}+\mathbf{v}$ (the "hypotenuse") is

$$
\begin{aligned}
||\mathbf{u}+\mathbf{v}||^2 &= \langle \mathbf{u}+\mathbf{v}, \mathbf{u}+\mathbf{v} \rangle \\
&= \langle \mathbf{u}, \mathbf{u}+\mathbf{v} \rangle + \langle \mathbf{v}, \mathbf{u}+\mathbf{v} \rangle && \text{by linearity of inner product in } 1^{st} \text{ argument} \\
&= \langle \mathbf{u}, \mathbf{u} \rangle + \langle \mathbf{u}, \mathbf{v} \rangle + \langle \mathbf{v}, \mathbf{u} \rangle + \langle \mathbf{v}, \mathbf{v} \rangle && \text{by symmetry and linearity} \\
&= ||\mathbf{u}||^2 + 2\langle \mathbf{u}, \mathbf{v} \rangle + ||\mathbf{v}||^2 && \text{by symmetry}
\end{aligned}
$$

The last expression is $||\mathbf{u}||^2 + ||\mathbf{v}||^2$ if and only if $\langle \mathbf{u}, \mathbf{v} \rangle = 0$.
We therefore define $\mathbf{u}$ and $\mathbf{v}$ to be *orthogonal* if $\langle \mathbf{u}, \mathbf{v} \rangle = 0$.
Pythagorean Theorem for vectors: if vectors $\mathbf{u}$ and $\mathbf{v}$ over the reals are orthogonal then $||\mathbf{u}+\mathbf{v}||^2 = ||\mathbf{u}||^2 + ||\mathbf{v}||^2$

Properties of orthogonality

To solve the Fire Engine Problem, we will use the Pythagorean Theorem in conjunction with the following simple observations:

Orthogonality Properties:

Property O1: If $\mathbf{u}$ is orthogonal to $\mathbf{v}$ then $\mathbf{u}$ is orthogonal to $\alpha\,\mathbf{v}$ for every scalar α.

Property O2: If $\mathbf{u}$ and $\mathbf{v}$ are both orthogonal to $\mathbf{w}$ then $\mathbf{u}+\mathbf{v}$ is orthogonal to $\mathbf{w}$.

Proof:

1. $\langle \mathbf{u}, \alpha\,\mathbf{v}\rangle = \alpha\,\langle \mathbf{u}, \mathbf{v}\rangle = \alpha\,0 = 0$
2. $\langle \mathbf{u}+\mathbf{v}, \mathbf{w}\rangle = \langle \mathbf{u}, \mathbf{w}\rangle + \langle \mathbf{v}, \mathbf{w}\rangle = 0 + 0$

Example: $[1,2]\cdot[2,-1] = 0$ so $[1,2]\cdot[20,-10] = 0$

Example:

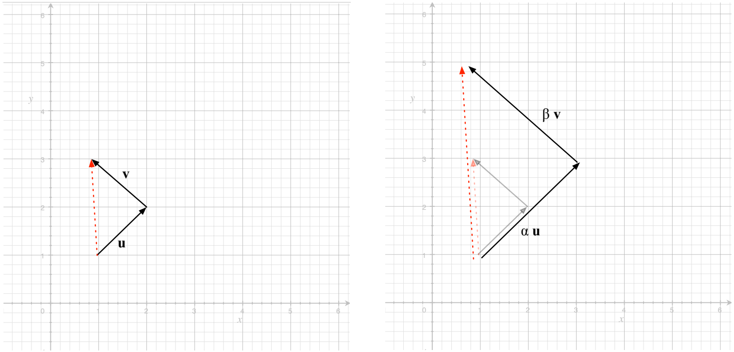
$$\begin{array}{rcl} [1,2,1]\cdot[1,-1,1] & = & 0 \\ [0,1,1]\cdot[1,-1,1] & = & 0 \\ \hline ([1,2,1]+[0,1,1])\cdot[1,-1,1] & = & 0 \end{array}$$

Length of sum of orthogonal vectors

Scaling orthogonal vectors gives us orthogonal vectors.

Lemma: If $\mathbf{u}$ is orthogonal to $\mathbf{v}$ then, for any scalars α, β,

$$||\alpha\,\mathbf{u} + \beta\,\mathbf{v}||^2 = \alpha^2||\mathbf{u}||^2 + \beta^2||\mathbf{v}||^2$$



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Proof:

$$\begin{aligned}
(\alpha\,\mathbf{u} + \beta\,\mathbf{v}) \cdot (\alpha\,\mathbf{u} + \beta\,\mathbf{v}) &= \alpha\,\mathbf{u} \cdot \alpha\,\mathbf{u} + \beta\,\mathbf{v} \cdot \beta\,\mathbf{v} + \alpha\,\mathbf{u} \cdot \beta\,\mathbf{v} + \beta\,\mathbf{v} \cdot \alpha\,\mathbf{u} \\
&= \alpha\,\mathbf{u} \cdot \alpha\,\mathbf{u} + \beta\,\mathbf{v} \cdot \beta\,\mathbf{v} + \alpha\beta\,(\mathbf{u} \cdot \mathbf{v}) + \beta\alpha\,(\mathbf{v} \cdot \mathbf{u}) \\
&= \alpha\,\mathbf{u} \cdot \alpha\,\mathbf{u} + \beta\,\mathbf{v} \cdot \beta\,\mathbf{v} + 0 + 0 \\
&= \alpha^2\,\|\mathbf{u}\|^2 + \beta^2\,\|\mathbf{v}\|^2
\end{aligned}$$

Mutual orthogonality

Definition: We say $\mathbf{v}_1, \ldots, \mathbf{v}_n$ are *mutually orthogonal* if $\mathbf{v}_i$ is orthogonal to $\mathbf{v}_j$ for every pair i, j such that $i \neq j$.

Example: $[1, 2, 1], [1, -1, 1], [1, 0, -1]$ are mutually orthogonal:

- $\langle [1, 2, 1], [1, -1, 1] \rangle = 0$
- $\langle [1, 2, 1], [1, 0, -1] \rangle = 0$
- $\langle [1, -1, 1], [1, 0, -1] \rangle = 0$

Lemma: If $\mathbf{u}$ is orthogonal to $\mathbf{v}$ then, for any scalars α, β,

$$||\alpha\,\mathbf{u} + \beta\,\mathbf{v}||^2 = \alpha_1^2||\mathbf{u}||^2 + \beta^2||\mathbf{v}||^2$$

generalizes to:

Lemma: If $\mathbf{v}_1, \ldots, \mathbf{v}_n$ are mutually orthogonal then, for any scalars $\alpha_1, \ldots, \alpha_n$,

$$||\alpha_1\mathbf{v}_1 + \cdots + \alpha_n\mathbf{v}_n||^2 = \alpha_1^2||\mathbf{v}_1||^2 + \cdots + \alpha_n^2||\mathbf{v}_n||^2$$

Orthogonality helps solve the *fire engine* problem

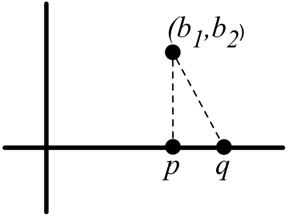
Fire Engine Lemma:

- Let $\mathbf{b}$ be a vector.
- Let $\mathbf{a}$ be a nonzero vector $\Rightarrow$ The set $\{\alpha\,\mathbf{a}\ :\ \alpha \in \mathbb{R}\}$ is a line L
- Let $\mathbf{p}$ be the point on the line L such that $\mathbf{b} - \mathbf{p}$ is orthogonal to $\mathbf{a}$.

Then $\mathbf{p}$ is the point on the line that is closest to $\mathbf{b}$.

Example: Line is the x-axis, i.e. the set $\{(x, y) : \ \ y = 0\}$, and point is (b_1, b_2).

Lemma states: closest point on the line is $\mathbf{p} = (b_1, 0)$.



- For any other point $\mathbf{q}$, the points (b_1, b_2), $\mathbf{p}$, and $\mathbf{q}$ form a right triangle.
- Since $\mathbf{q}$ is different from $\mathbf{p}$, the base is nonzero.
- By the Pythagorean Theorem, the hypotenuse's length is greater than the height.
- This shows that $\mathbf{q}$ is farther from (b_1, b_2) than $\mathbf{p}$ is.

Orthogonality helps solve the *fire engine* problem

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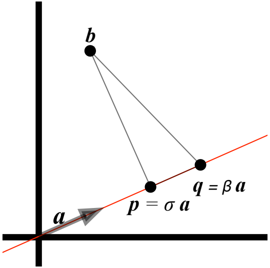
Then $\mathbf{p}$ is the point on the line that is closest to $\mathbf{b}$.

Proof: Let $\mathbf{q}$ be any point on L. The three points $\mathbf{q}$, $\mathbf{p}$, and $\mathbf{b}$ form a triangle.

- Since $\mathbf{p}$ and $\mathbf{q}$ are both on L, they are both multiples of $\mathbf{a}$, so their difference $\mathbf{p} - \mathbf{q}$ is also a multiple of $\mathbf{a}$.
- Since $\mathbf{b} - \mathbf{p}$ is orthogonal to $\mathbf{a}$, therefore, it is also orthogonal to $\mathbf{p} - \mathbf{q}$



Orthogonality helps solve the *fire engine* problem

Fire Engine Lemma:

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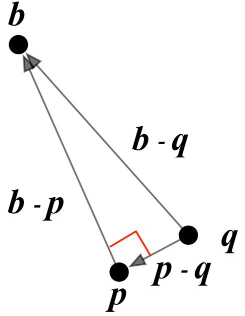
Proof: Let $\mathbf{q}$ be any point on L. The three points $\mathbf{q}$, $\mathbf{p}$, and $\mathbf{b}$ form a triangle.



- Since $\mathbf{p}$ and $\mathbf{q}$ are both on L, they are both multiples of $\mathbf{a}$, so their difference $\mathbf{p} - \mathbf{q}$ is also a multiple of $\mathbf{a}$.
- Since $\mathbf{b} - \mathbf{p}$ is orthogonal to $\mathbf{a}$, therefore, it is also orthogonal to $\mathbf{p} - \mathbf{q}$
- Hence by the Pythagorean Theorem,

$$||\mathbf{b} - \mathbf{q}||^2 = ||\mathbf{p} - \mathbf{q}||^2 + ||\mathbf{b} - \mathbf{p}||^2$$

- If $\mathbf{q} \neq \mathbf{p}$ then $||\mathbf{p} - \mathbf{q}||^2 > 0$ so $||\mathbf{b} - \mathbf{p}|| < ||\mathbf{b} - \mathbf{q}||$.

Decomposition of $\mathbf{b}$ into parallel and perpendicular components

Lemma states: among all the points on the line $\{\alpha\,\mathbf{a} \;:\; \alpha \in R\}$, the closest to $\mathbf{b}$ is the point $\mathbf{p}$ on such that $\mathbf{b} - \mathbf{p}$ is orthogonal to $\mathbf{a}$.

Definition: For any vector $\mathbf{b}$ and any vector $\mathbf{a}$, define vectors $\mathbf{b}^{||\mathbf{a}}$ and $\mathbf{b}^{\perp\mathbf{a}}$ to be the *projection of* $\mathbf{b}$ *onto Span* $\{\mathbf{a}\}$ and the *projection of* $\mathbf{b}$ *orthogonal to* $\mathbf{a}$ if

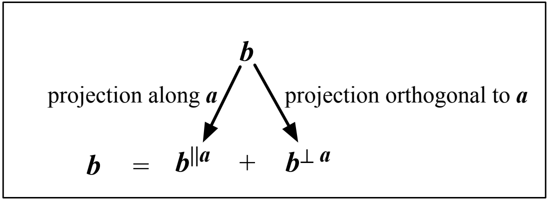
$$\mathbf{b} = \mathbf{b}^{||\mathbf{a}} + \mathbf{b}^{\perp\mathbf{a}}$$

and there is a scalar $\sigma \in R$ such that

$$\mathbf{b}^{||\mathbf{a}} = \sigma\,\mathbf{a}$$

and

$$\mathbf{b}^{\perp\mathbf{a}} \text{ is orthogonal to } \mathbf{a}$$



Closest-Point Corollary

For any vector $\mathbf{b}$ and any vector $\mathbf{a}$, define vectors $\mathbf{b}^{||\mathbf{a}}$ and $\mathbf{b}^{\perp\mathbf{a}}$ ....

$$\mathbf{b} = \mathbf{b}^{||\mathbf{a}} + \mathbf{b}^{\perp\mathbf{a}}$$

and there is a scalar $\sigma \in R$ such that

$$\mathbf{b}^{||\mathbf{a}} = \sigma\,\mathbf{a}$$

and

$$\mathbf{b}^{\perp\mathbf{a}} \text{ is orthogonal to } \mathbf{a}$$

Closest-Point Corollary: For any vector $\mathbf{b}$ and vector $\mathbf{a}$ over the reals,

- the point in Span $\{\mathbf{a}\}$ that is closest to $\mathbf{b}$ is the projection $\mathbf{b}^{||\mathbf{a}}$ onto Span $\{\mathbf{a}\}$,
- and the distance between that point and $\mathbf{b}$ is $\|\mathbf{b}^{\perp\mathbf{a}}\|$, the norm of the projection of $\mathbf{b}$ orthogonal to $\mathbf{a}$.

Decomposition of $\mathbf{b}$ into parallel and perpendicular components: example

For any vector $\mathbf{b}$ and any vector $\mathbf{a}$, define vectors $\mathbf{b}^{||\mathbf{a}}$ and $\mathbf{b}^{\perp\mathbf{a}}$ ....

$$\mathbf{b} = \mathbf{b}^{||\mathbf{a}} + \mathbf{b}^{\perp\mathbf{a}}$$

and there is a scalar $\sigma \in R$ such that

$$\mathbf{b}^{||\mathbf{a}} = \sigma\, \mathbf{a}$$

and

$$\mathbf{b}^{\perp\mathbf{a}} \text{ is orthogonal to } \mathbf{a}$$

Example: What if $\mathbf{a}$ is the zero vector?
In this case, the only vector $\mathbf{b}^{||\mathbf{a}}$ satisfying the second equation is the zero vector.
According to first equation, $\mathbf{b}^{\perp\mathbf{a}}$ must equal $\mathbf{b}$.
Fortunately, this choice of $\mathbf{b}^{\perp\mathbf{a}}$ does satisfy third equation: $\mathbf{b}^{\perp\mathbf{a}}$ is orthogonal to $\mathbf{a}$.
Indeed, *every* vector is orthogonal to $\mathbf{a}$ when $\mathbf{a}$ is the zero vector.
What is the point in Span $\{\mathbf{0}\}$ closest to $\mathbf{b}$?
The *only* point in Span $\{\mathbf{0}\}$ is the zero vector...
so that must be the closest point to $\mathbf{b}$, and the distance to $\mathbf{b}$ is $||\mathbf{b}||$.

Computing the projections

$\mathbf{b} = \mathbf{b}^{||\mathbf{a}} + \mathbf{b}^{\perp\mathbf{a}}$ $\qquad$ $\mathbf{b}^{||\mathbf{a}} = \sigma\,\mathbf{a}$ $\qquad$ $\mathbf{b}^{\perp\mathbf{a}}$ is orthogonal to $\mathbf{a}$

If $\mathbf{a} = \mathbf{0}$ then $\mathbf{b}^{||\mathbf{a}} = \mathbf{0}$

What if $\mathbf{a} \neq \mathbf{0}$? Need to compute σ....

- $\left\langle \mathbf{b}^{\perp\mathbf{a}}, \mathbf{a} \right\rangle = 0$. Substitute for $\mathbf{b}^{\perp\mathbf{a}}$: $\left\langle \mathbf{b} - \mathbf{b}^{||\mathbf{a}}, \mathbf{a} \right\rangle = 0$.
- Substitute for $\mathbf{b}^{||}$: $\langle \mathbf{b} - \sigma\,\mathbf{a}, \mathbf{a} \rangle = 0$.
- Using linearity and homogeneity of inner product,

$$\langle \mathbf{b}, \mathbf{a} \rangle - \sigma\,\langle \mathbf{a}, \mathbf{a} \rangle = 0$$

- Solving for σ, we obtain

$$\sigma = \frac{\left\langle \mathbf{b},\mathbf{a} \right\rangle}{\langle \mathbf{a},\mathbf{a} \rangle}$$

In the special case in which $\|\mathbf{a}\| = 1$, the denominator $\langle \mathbf{a}, \mathbf{a} \rangle = 1$ so

$$\sigma = \langle \mathbf{b}, \mathbf{a} \rangle$$

Quiz: Write `project_along(b, a)` to return the vector $\mathbf{b}^{||\mathbf{a}}$

Computing the projections

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Quiz: Write `project_along(b, a)` to return the vector $\mathbf{b}^{||\mathbf{a}}$

Answer: `def project_along(b, a):  return ((b*a)/(a*a))*a` $\qquad$ Almost.

Computing the projections

$\mathbf{b} = \mathbf{b}^{||\mathbf{a}} + \mathbf{b}^{\perp\mathbf{a}}$ $\quad$ $\mathbf{b}^{||\mathbf{a}} = \sigma\, \mathbf{a}$ $\quad$ $\mathbf{b}^{\perp\mathbf{a}}$ is orthogonal to $\mathbf{a}$

If $\mathbf{a} = \mathbf{0}$ then $\mathbf{b}^{||\mathbf{a}} = \mathbf{0}$

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- Substitute for $\mathbf{b}^{||}$: $\langle \mathbf{b} - \sigma\, \mathbf{a}, \mathbf{a} \rangle = 0$.
- Using linearity and homogeneity of inner product,

$$\langle \mathbf{b}, \mathbf{a} \rangle - \sigma\, \langle \mathbf{a}, \mathbf{a} \rangle = 0$$

- Solving for σ, we obtain

$$\sigma = \frac{\langle \mathbf{b}, \mathbf{a} \rangle}{\langle \mathbf{a}, \mathbf{a} \rangle}$$

In the special case in which $\|\mathbf{a}\| = 1$, the denominator $\langle \mathbf{a}, \mathbf{a} \rangle = 1$ so

$$\sigma = \langle \mathbf{b}, \mathbf{a} \rangle$$

Quiz: Write `project_along(b, a)` to return the vector $\mathbf{b}^{||\mathbf{a}}$

Answer: `def project_along(b, a): return ((b*a)/(a*a))*a` Almost.

Best:

```
def project_along(b, a): return ((b*a)/(a*a) if a*a != 0 else 0)*a
```

Computing the projections

$\mathbf{b} = \mathbf{b}^{||\mathbf{a}} + \mathbf{b}^{\perp\mathbf{a}}$ $\mathbf{b}^{||\mathbf{a}} = \sigma\,\mathbf{a}$ $\mathbf{b}^{\perp\mathbf{a}}$ is orthogonal to $\mathbf{a}$

- $\sigma = \dfrac{\langle \mathbf{b}, \mathbf{a} \rangle}{\langle \mathbf{a}, \mathbf{a} \rangle}$
- However, if $\mathbf{a} = \mathbf{0}$ then $\sigma = 0$.
- ```
  def project_along(b, a):
      sigma = (b*a)/(a*a) if a*a != 0 else 0
      return sigma * a
  ```

Quiz: Use `project_along(b, a)` to write the procedure

`project_orthogonal_1(b, a)`

that returns $\mathbf{b}^{\perp\mathbf{a}}$
  ```

Computing the projections

$\mathbf{b} = \mathbf{b}^{||\mathbf{a}} + \mathbf{b}^{\perp\mathbf{a}}$ $\mathbf{b}^{||\mathbf{a}} = \sigma\,\mathbf{a}$ $\mathbf{b}^{\perp\mathbf{a}}$ is orthogonal to $\mathbf{a}$

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- ```
  def project_along(b, a):
   sigma = (b*a)/(a*a) if a*a != 0 else 0
   return sigma * a
  ```

Quiz: Use `project_along(b, a)` to write the procedure

`project_orthogonal_1(b, a)`

that returns $\mathbf{b}^{\perp\mathbf{a}}$

```
def project_orthogonal_1(b, a):  return b - project_along(b, a)
```
```

Projecting along "nearly zero" vectors

Mathematically, this procedure is correct:

```
def project_along(b, a):
  sigma = (b*a)/(a*a) if a*a != 0 else 0
  return sigma * a
```

However, because of floating-point roundoff error, we need to make a slight change.

Often the vector **a** will be not a truly zero vector but practically it will be zero.

If the entries of **a** are tiny, the procedure should treat **a** as a zero vector: `sigma` should be assigned zero.

We will consider **a** to be a zero vector if its squared norm is no more than, say, 10^{-20}.

Revised version:

```
def project_along(b, a):
  sigma = (b*a)/(a*a) if a*a > 1e-20 else 0
  return sigma * a
```

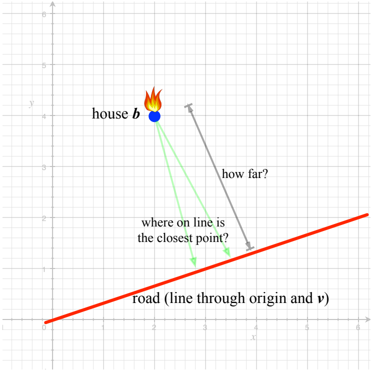
Solution to the *fire engine* problem

Example:

$\mathbf{a} = [6, 2]$ and $\mathbf{b} = [2, 4]$.

The closest point on the line $\{\alpha\, \mathbf{a} \ : \ \alpha \in \mathbb{R}\}$ is the point $\mathbf{b}^{||\mathbf{a}} = \sigma\, \mathbf{a}$ where

$$\begin{aligned} \sigma &= \frac{\mathbf{a} \cdot \mathbf{b}}{\mathbf{a} \cdot \mathbf{a}} \\ &= \frac{6 \cdot 2 + 2 \cdot 4}{6 \cdot 6 + 2 \cdot 2} \\ &= \frac{20}{40} \\ &= \frac{1}{2} \end{aligned}$$



Thus the point closest to $\mathbf{b}$ is $\frac{1}{2}\,[6, 2] = [3, 1]$.
The distance to $\mathbf{b}$ is

$$\|\mathbf{b}^{\perp\mathbf{a}}\| = \|[2, 4] - [3, 1]\| = \|[-1, 3]\| = \sqrt{10}$$

which is just under 3.5, the length of the firehose.
The house is saved!

Best approximation

The *fire engine* problem can be restated as finding the vector on the line that "best approximates" the given vector $\mathbf{b}$.

By "best approximation", we just mean closest.

This notion of "best approximates" comes up again and again:

- in least-squares, a fundamental data analysis technique,
- image compression,
- in principal component analysis, another data analysis technique, and
- in latent semantic analysis, an information retrieval technique.

Towards solving the higher-dimensional version of *best approximation*

The fire engine problem can be stated thus:

> **Computational Problem:** *Closest point in the span of a single vector*
> Given a vector $\mathbf{b}$ and a vector $\mathbf{a}$ over the reals, find the vector in Span $\{\mathbf{a}\}$ closest to $\mathbf{b}$.

A natural generalization of the *fire engine* problem is this:

> **Computational Problem:** *Closest point in the span of several vectors*
> Given a vector $\mathbf{b}$ and vectors $\mathbf{a}_1, \ldots, \mathbf{a}_n$ over the reals, find the vector in Span $\{\mathbf{a}_1, \ldots, \mathbf{a}_n\}$ closest to $\mathbf{b}$.

We will study this problem next.